SUSTAINABLE URBAN WATER USE WITH A GIS PLANNING SUPPORT SYSTEM: A CASE STUDY OF METROPOLITAN ATLANTA, GEORGIA

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SUSTAINABLE URBAN WATER USE WITH A GIS PLANNING SUPPORT SYSTEM: A CASE STUDY OF METROPOLITAN ATLANTA, GEORGIA

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To my loving father, mother, and younger brother

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SUMMARY

Sustainable water use management is an imperative task for local and regional planning authorities. Although water use is related to land use types and the physical characteristics of the built environment, few studies have examined the relationship between growth policies and sustainable water use. This dissertation discusses a sustainable water use framework, including chief determinants of water consumption. It presents sample analyses of sustainable water uses and demonstrates a GIS-based planning support system that includes integrated land use-water models, called 'Sustainable Water use Scenario-based Planning Support Systems' (SWSPSS).

The major research questions in this study are: (1) What are the relationships between urban form/urban development and urban water use? (2) What are the implications of incorporating land-use variables into water-use planning? (3) How can planners formulate sustainable urban water use projections by adding knowledge about local water use and land development patterns? (4) How can planners benefit from an integrated water-land use model, and (5) Which approach is more effective in creating more sustainable water use: a land use-development (urban form) approach or a technological solutions (including rain water harvesting) approach?

This study is composed of three linked research analyses: a cross-sectional regression analysis to examine the relationship between key water measures with county water withdrawal data; an empirical analysis adopting a spatial error model using single family residential water billing data; and the development of sustainable water use sample analysis based on local water use profiles and rainwater harvesting (RWH) potential. This analysis establishes the foundation for the development of an ArcGIS-based planning support system using Python scripting and ModelBuilder to forecast future water demand. . The system is then tested on a case study area consisting of 13 counties in the Atlanta metropolitan region.

The analyses find that a series of urban form variables associated with sprawl and low-density development configurations (population density, percent of single family housing, lot size) are correlated to water use rates. These results support the proposition that a compact growth policy that promotes high density and a mixture of residential types would reduce per capita urban water use in the long run. The case study demonstrates the potential change in water use in a large metropolitan area. The major contribution of this research is to connect land use to water resource planning and to demonstrate that changes in urban form can result in more sustainable water use.

CHAPTER 1

INTRODUCTION

Water is one of the essential resources that cities and regions need to support urban growth. Water is a non-replaceable resource and an absolute necessity for human living with no other alternative. It is also frequently subsidized for municipal and agricultural customers (Wentz and Gober 2007).

According to U.S. Geological Survey and U.S. Department of the Interior, water use in the U.S. in 2010 was estimated to be about 355 billion gallons per day (Bgal/d) (Maupin, Kenny et al. 2014). Total water withdrawal has rapidly increased due to population and economic growth for last 60 years in the U.S., although it exhibited a steady trend since 1985 (Figure 1). More recently, total withdrawals in 2010 were 13 percent less than in 2005 caused by significant declines in the largest category of the use, thermoelectric power. Withdrawals at power plants have declined in some states due to the implementation of new rules for water-efficient cooling technology and/or conversion to dry cooling systems (Maupin, Kenny et al. 2014).

Despite of this recent downward trend, the largest growth of water demand still occurs in urbanized areas due to greater population and economic activities (Fitzhugh and Richter 2004). The percentage of the population served by public-supply withdrawals has increased from 62 percent in 1950 to 86 percent in 2010 (Maupin, Kenny et al. 2014). Besides in the last decade, because the population growth rate was much faster in Southern and Western States (14.3 and 13.8 percent, respectively) compared to

Midwestern States (3.9 percent) and Northeastern States (3.2 percent) (Maupin, Kenny et al. 2014), more attention is needed for the water use trend in urbanized areas, especially in urbanized areas in Southern and Western States.

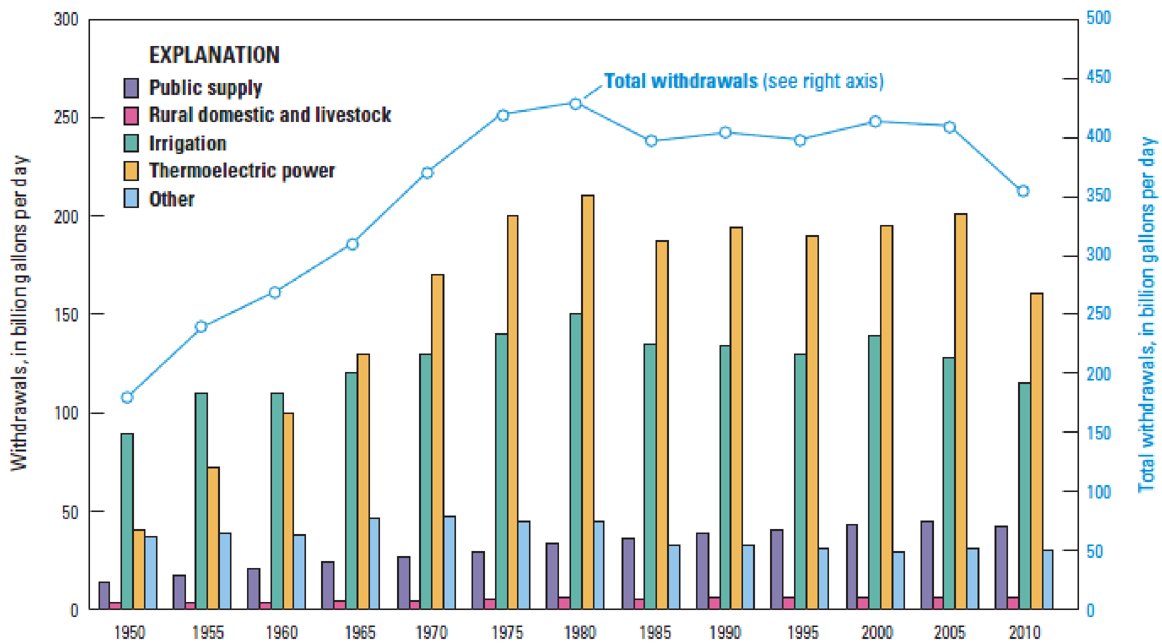


Figure 1. Trends in Total Water Withdrawals by Water-use Category, 1950-2010 (Maupin et al and USGS, 2010; page 46)

CONFLICT OVER WATER USE: TRI-STATE WATER WARS

Historically, water has frequently been the source of competition or controversy when demands are unmet by supply (Arbués, García-Valiñas et al. 2003) and the locality or region faces unexpected water shortages in times of drought. As mentioned earlier, many urban areas in the western and southern regions of the U.S are likely to face conflict over water to sustain growth. Especially, the conflict over water resources among three southeastern states, Alabama, Georgia, and Florida, commonly called ‘Tri-state water wars’, is the example of competition and controversy for water resources at the regional scale. For the last two decades, Alabama, Georgia, and Florida have battled over the allocation of water in two major river basins (the Alabama-Coosa-Tallapoosa and the Apalachicola-Chattahoochee-Flint basins) crossing their borders (Figure 2).

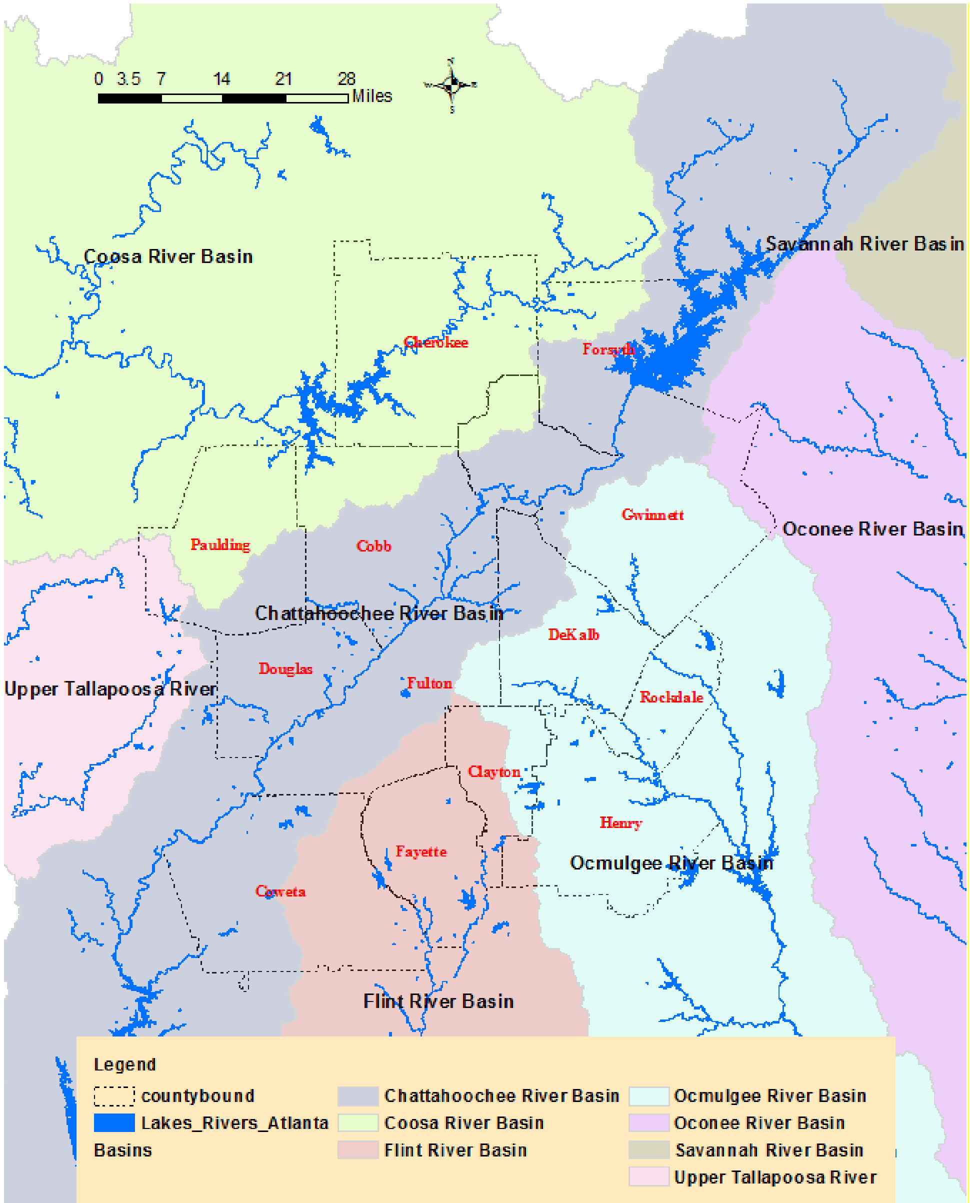


Figure 2. Water Resources and Basins in the Metropolitan Atlanta Area

Alabama needed water for agriculture, industry, fisheries and preservation of habitats, and power generation, whereas Florida requires freshwater flows into Apalachicola Bay to maintain salinity balances for fisheries (Missimer, Danser et al.

2014). Georgia is primarily interested in maintenance and expansion of water supplies to meet the needs of the Metropolitan Atlanta region and other cities, including power generation and recreation. In 1990 Alabama filed a lawsuit, later joined by Florida, to ban the US Army Corps of Engineers (USACE) from creating water supply rights from Lake Lanier, the major and almost only water supply source for Metropolitan Atlanta region. In Metropolitan Atlanta, GA, more than 5 million population in 16 counties and 90 cities in metro region rely heavily on surface water withdrawn from Lake Lanier. This battle has resulted in a series of litigation attacks and counter attacks among the three states; the judicial decision in the Federal District Court in 2009 (US District Court 2009) that put Georgia in challenge securing water supply source from Lake Lanier; a overruling by US Circuit Court of Appeals (2010); a refusal of the US Supreme Court (2013) to overrule the Circuit Court of Appeals; and the following lawsuit filed by Florida against State of Georgia.

Furthermore, the water crises due to below-average rainfall and in consecutive years from 2005 to 2008 in Northern Georgia caused a severe drop in the level of Lake Lanier, causing a reduction of the lake stage to a critical level in 2007, triggering a level 4 drought emergency (Missimer, Danser et al. 2014) (Figure 3). The lake level dropped 15 feet low its peak stage in October 2007 (Glennon 2009) and this reduction in the volume of stored water put Metropolitan Atlanta region into a severe water crisis, with a prediction that Lake Lanier would be depleted within 3-4 months (Missimer, Danser et al. 2014). Because there was no backup water supply except Lake Lanier for Metropolitan Atlanta region, this was and remains an extremely critical issue in the region in terms of both water resource management and sustainable growth from a planning perspective.

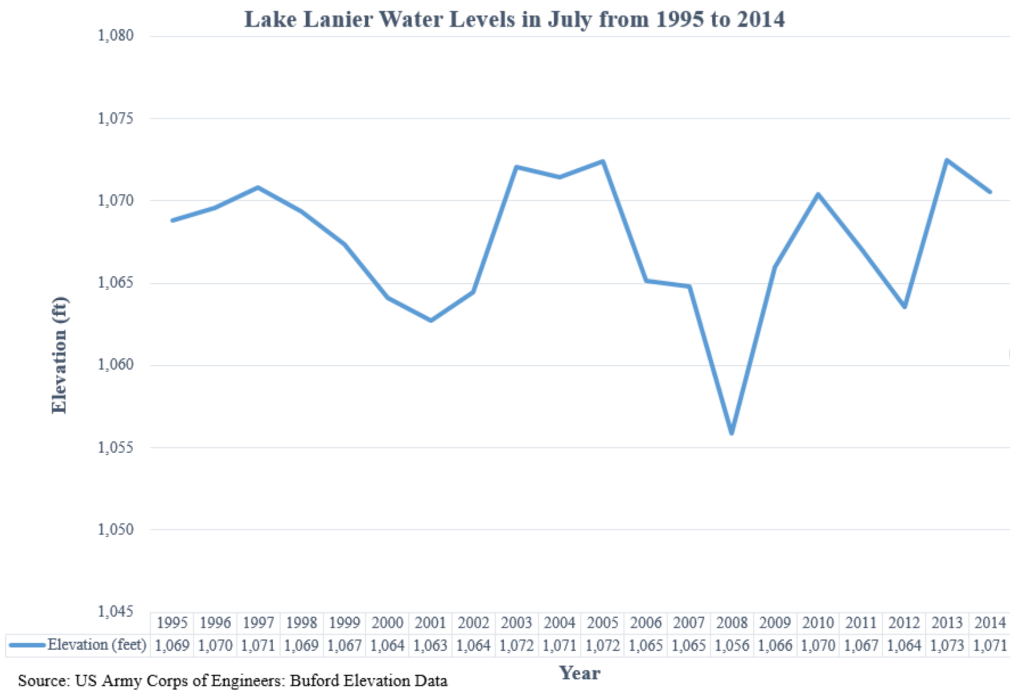


Figure 3. Lake Lanier Water Levels (Source: Buford Elevation Data, U.S. Army Corps of Engineers, http://water.sam.usace.army.mil/gage/bufelev.htm, Accessed April 2016)

Atlanta Regional Commission (ARC, hereafter), the regional planning agency, expects the population to increase from 4.55 million in 2010 to 6.84 million in 2040 (Table 1).

Table 1. Population Change in 13 Counties in the Metropolitan Atlanta (ARC Plan2040 Forecast)

COUNTY	Year 2010	Year 2020	Year 2030	Year 2040	Year 2010 - 2040
Cherokee	214,346	267,877	332,649	392,411	178,065
Clayton	259,424	278,857	300,720	327,552	68,128
Cobb	688,078	739,106	801,831	885,062	196,984
Coweta	127,317	163,781	205,753	239,808	112,491
DeKalb	691,893	725,987	797,405	874,424	182,531
Douglas	132,403	148,306	174,525	201,325	68,922
Fayette	106,567	113,128	126,837	143,255	36,688
Forsyth	175,511	254,275	353,748	430,301	254,790
Fulton	920,581	1,017,903	1,139,008	1,264,376	343,795
Gwinnett	805,321	951,162	1,146,091	1,350,358	545,037
Henry	203,922	250,746	306,381	351,691	147,769
Paulding	142,324	167,843	211,855	259,578	117,254
Rockdale	85,215	96,715	112,106	128,103	42,888
Total	4,552,902	5,175,686	6,008,909	6,848,244	2,295,342

Considering the continuing influx of population to the Metropolitan Atlanta region, legal dispute among three States, and water crisis due to drought, the challenges regarding water resources for Metropolitan Atlanta is likely to continue into the next generation. Metropolitan Atlanta is very likely to face substantial challenges in maintaining economic growth and a quality of life unless certain long term policy and planning actions are implemented. Therefore, there is a need for extensive discussion for sustainable water use management that would support economic growth, prosperity and healthy life for the metropolitan area.

MOTIVATION OF DISSERTATION STUDY

The situation for most urbanized cities and metropolitan areas in the U.S. are not much different from the case of metropolitan Atlanta. Although individual water use levels (or gallon per capita use) in US have been gradually declined for last decades, the increase of population, urbanization, sprawl, and decay of existing conventional infrastructure continuously raise water issues in urban areas in the U.S.

In general, water use is closely tied to land use types and the physical characteristics of the built environment. Literature discussing water use drivers suggests that there are substantial relationships between these variables at different geographic scales. If such a relationship exists, planners can influence local water-use patterns through tools not directly related to water planning, such as zoning regulations and urban growth policy. Zoning regulation affects various properties of urban development configuration such as land uses types, density of land uses, residential types, and infrastructure provisions and so on. If there are substantial relationships between urban development configuration variables and water use patterns, planners can strengthen sustainable water use management planning actions by suggesting reasonable goals in controlling urban density and development configuration. Such actions imply that planning authorities and planners can engage water use management for sustainable community more actively.

Besides, if land use types and the magnitude of water use can be connected, planners can not only project future water use demand, but also visualize the geographical pattern of water use. This will greatly improve their ability to communicate with stakeholders, interest groups, and water resource management planning agencies.

PURPOSE OF STUDY AND CONCEPTUAL FRAMEWORK

This study focuses on the potential role of planning for sustainable water use. It proposes that a sustainable water use framework should connect land use and water resource planning. It illustrates how integrated water-land use demand forecasting models could be used for sustainable water use planning. Specifically, this study investigates whether making changes on urban form-urban development configuration would affect water use and if this 'land use-development configuration approach' is effective compared to other conservation policies related to water device efficiency improvement, namely the 'technological approach'. This study also aims to demonstrate that community or local government can follow a sustainable water use path when two approaches are combined. Figure 4 shows the conceptual framework how sustainable water use policies would lead the community to more alternative path.

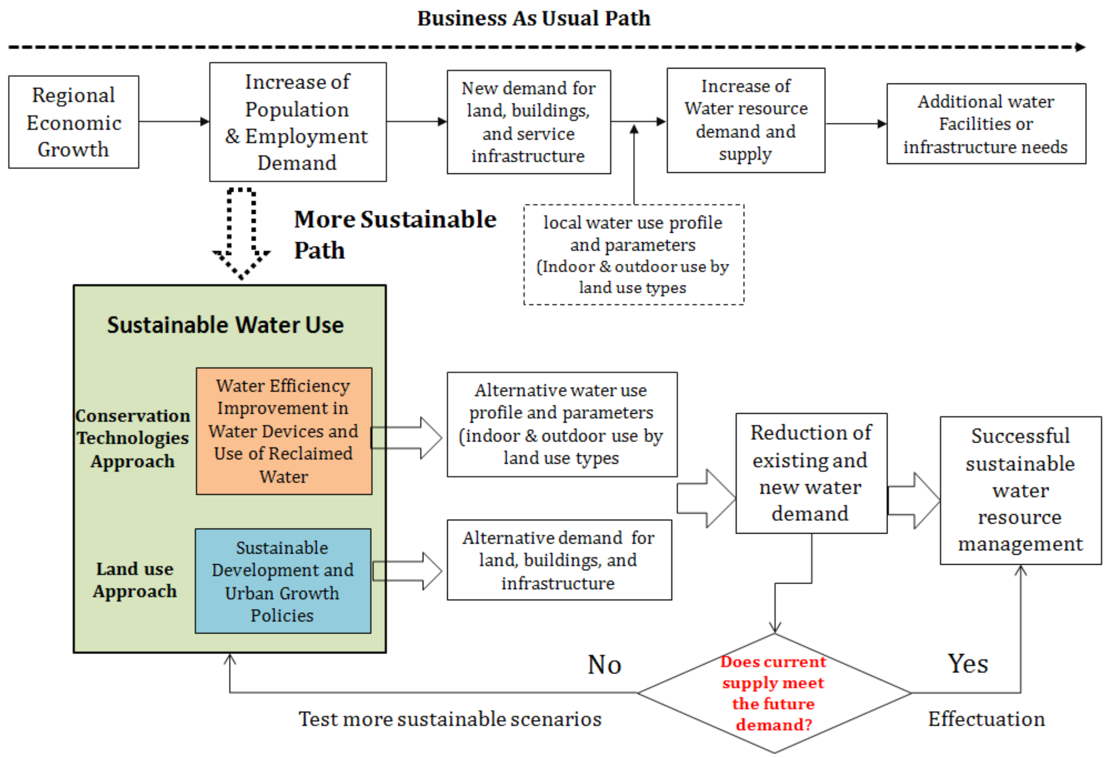


Figure 4: Conceptual Framework: Sustainable Water Use Policies and Future Changes

RESEARCH QUESTIONS

The above goals lead to the following research questions:

(1) What are the relationships between urban form/urban development and urban water use?

(2) What are the implications of incorporating land-use variables into water-use planning?

(3) How can planners formulate sustainable urban water use projections by adding knowledge about local water use and land development patterns?

(4) How can planners benefit from an integrated water-land use model to promote local and regional water sustainability?

(5) Which approach is more effective in creating more sustainable water use: a land use-development (urban form) approach or technological solutions (including rain water harvesting) approach?

SIGNIFICANCE OF STUDY

The current practice of sustainable water use and demand forecasting has focused on the short-term impacts in complex statistical models and conservation impact by water efficiency improvement, namely a ‘technological approach’. There is less research on the utility of a ‘land use-development configuration approach,’ which is associated with impact on water demand by urban form and urban growth policy controls. The unique contribution of this dissertation is to connect these two separate areas of research: land use and water resource planning. This study also aims to develop a Planning Support Systems (PSS, hereafter) that integrates GIS models and water demand projection functions for long term sustainable water planning. The PSS developed in this study demonstrates how simple models and tools and Python script can be used to develop a GIS application to conduct geoprocessing tasks and demand calculation tasks.

SCOPE OF STUDY

This dissertation study is composed of several research efforts designed to understand connection between sustainable water use and the control variables of urban form and development configurations. In the first empirical analysis, Chapter 3, this study focuses on the counties in the U.S as a geographic scope of study discussing county water use levels in urban areas. In the second and third empirical analyses, Chapters 4 and 5, the geographic scope of study are Fulton County in Georgia and the Metropolitan Atlanta region, respectively. In the second analysis, water use at parcel level is analyzed.

In the third analysis, thirteen counties in Metropolitan Atlanta are chosen to make up the case study area.

STRUCTURE OF STUDY

In order to discuss the long-term water demand with sustainability, this dissertation study is composed of chapters including literature and three main analyses at different geographic scales. First, this research begins with literature review (Chapter 2) to discuss theoretical background of sustainable water use, research gaps, and motivation of this dissertation research. Next, Chapter 3 discussed how a series of development configuration, socio-economic, and climate variables at county levels are statistically related to urban water use. In particular, a series of variables of interest related to urban form and land use configuration includes population density, a percentage of single family housings. This study assumes they are related to county representative individual water use level in the U.S. (gallon per capita per day, GPCD hereafter).

In Chapter 4 this dissertation also examines the relationship between residential water use and one of the most important spatially explicit variables, the size of residential lots. The residential lot size is a representative variables of low-density development patterns and urban sprawl. For example, a single family resident on a large lot would be more likely to consume more water, due to excessive water use for watering lawns and outdoor gardens and outdoor pools in the spring and summer seasons. If this is true, we can hypothesize that reducing typical residential lot size should be able to reduce residential water use.

Chapter 5 discusses how sustainable scenarios based on the Metropolitan Atlanta situation can be developed. Because SWSPSS requires a series of parameters in individual analysis modules in the system, this study develops hypothetical scenarios to be tested in a SWSPSS in Chapter 6. The parameters in scenarios reflect both current urban development configuration characteristics in study area and the local water use profile including possible ranges for parameter changes for sustainable water use. The scenarios used in analysis inevitably have to include many assumptions because there is considerable uncertainty in determining individual and aggregated water consumer's current and future water use behavior.

Chapter 6 demonstrates how GIS applications and multiple water use scenarios can be applied to project long-term local water consumption. As an extension of planning support system discussions that have existed for decades, this dissertation study shows how current GIS technologies, Python language, and simple spreadsheet applications can help planners generate useful information for in-depth discussion in local and regional sustainable water use plans. This chapter explains how the SWSPSS, which projects future water demand based on different urban growth and conservation scenarios, is developed. The SWSPSS can be a useful tool as a planning support systems (PSS) that provides 'useful information' to planners that they can communicate with public and interest groups when discussing long term water management plans.

Figure 5 summarizes the major steps and structure of this dissertation research.

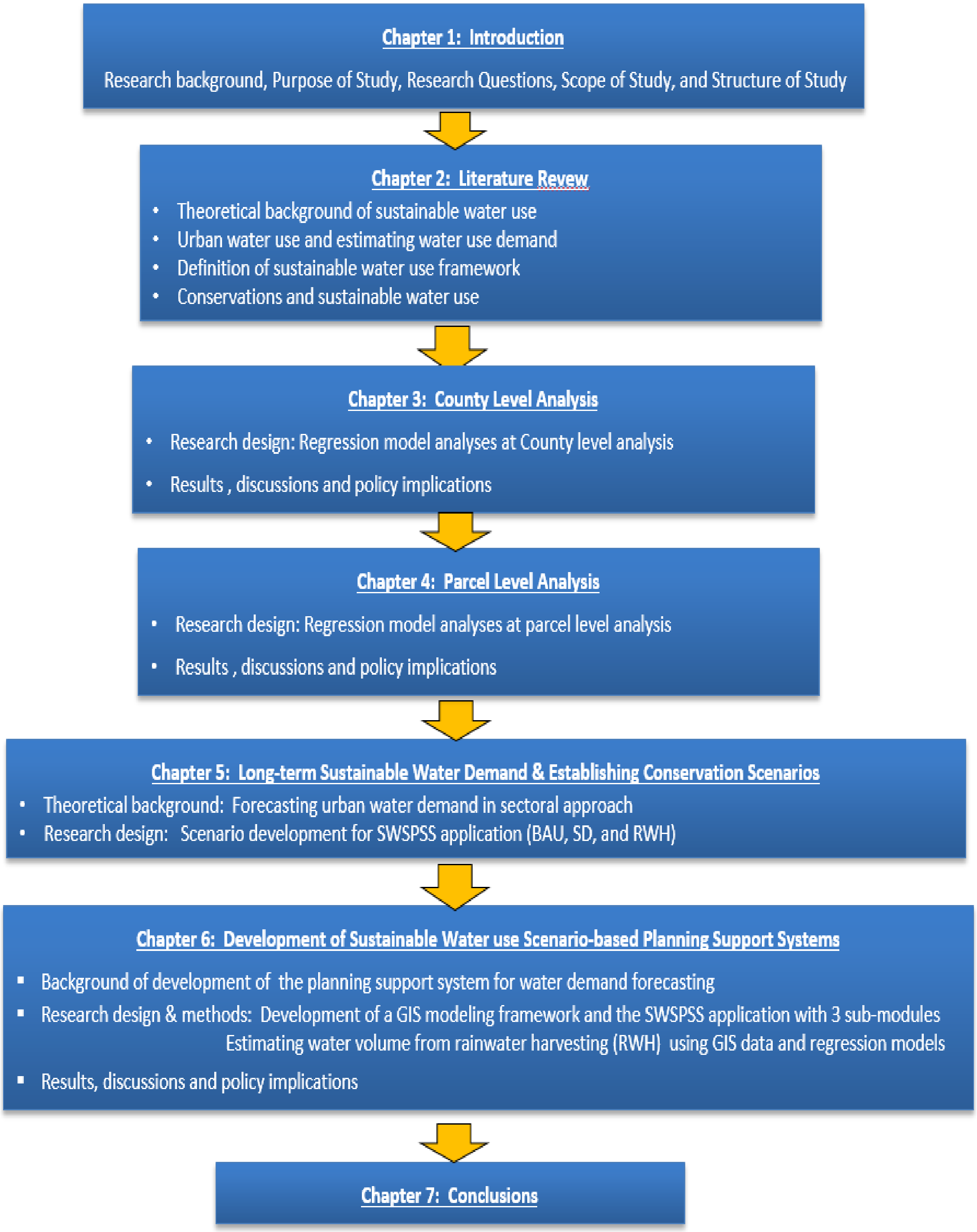


Figure 5. Structure of Study and Research Framework

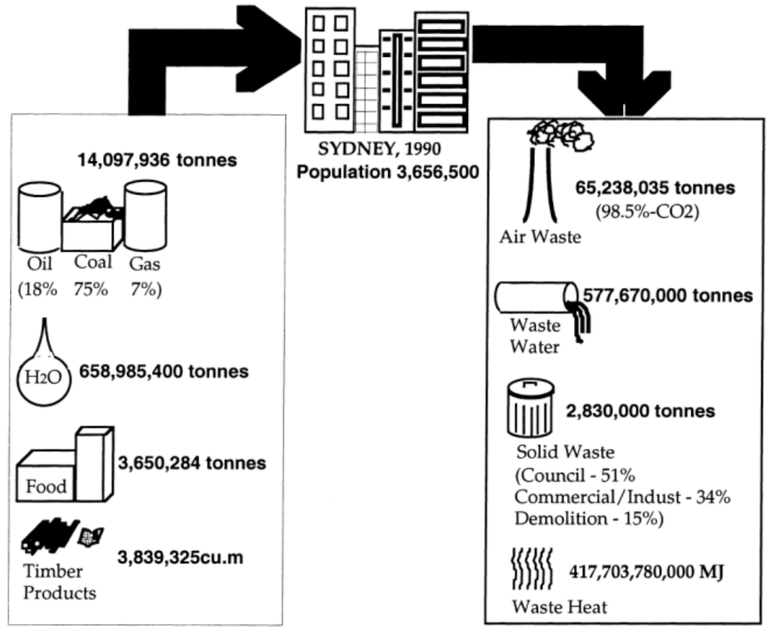
CHAPTER 2

LITERATURE REVIEW

THEORETICAL BACKGROUND OF SUSTAINABLE WATER USE

URBAN RESOURCE CONSUMPTION AND METABOLISM

Discussions of sustainability and consumption at the metropolitan level are rooted in the concept of the urban metabolism (Wolman 1965). Metabolism is an approach to understand cities as interconnected eco-biological systems, emphasizing the resource inputs and waste outputs of these settlements (Wolman 1965, Newman 1996). Wolman attempted to quantify flows of energy, water, materials, and wastes in a hypothetical American urban region of one million people. A handful of urban metabolism studies have been conducted to follow his pioneering discussion on metabolism in urban regions. Sahely et al. (2003) studied the metabolism of Toronto, Ontario, Canada, and found that the city's metabolism increased between 1987 and 1999 (Sahely, Dudding et al. 2003). Their study also used sustainability and metabolism concepts to develop an environmental and sustainability indicator in terms of water use modeling development (Sahely, Kennedy et al. 2005, Sahely and Kennedy 2007). As shown in Figure 6, Newman's studies, by identifying per-capita, inputs and waste outputs of Sydney, New South Wales, Australia, provide a snapshot of how cities consume natural resources and produce different types of wastes (Newman 1999).



Notes:
Waste water data do not include stormwater
Timber products and food data derived from national per capita data

Figure 6: Resource Inputs Consumed and Waste Outputs Discharged from Sydney, 1990 (Source: Newman, 1999)

As shown in Newman's example, water is the largest component of urban metabolism in terms of input and output quantity (Kennedy, Cuddihy et al. 2007). Most of the water inflow is either discharged as wastewater or lost by watering lawns. According to Kennedy and his colleagues' study (2007) based on selected world cities, waste water represents between 75 percent and 100 percent of the mass of water inflow. Newman (1999) also suggested "the extended metabolism model of the city" to include the settlement dynamics. Newman's diagram of extended metabolism model suggests that different types of human settlement may result in different levels of waste outputs and livability layouts (Figure 7).

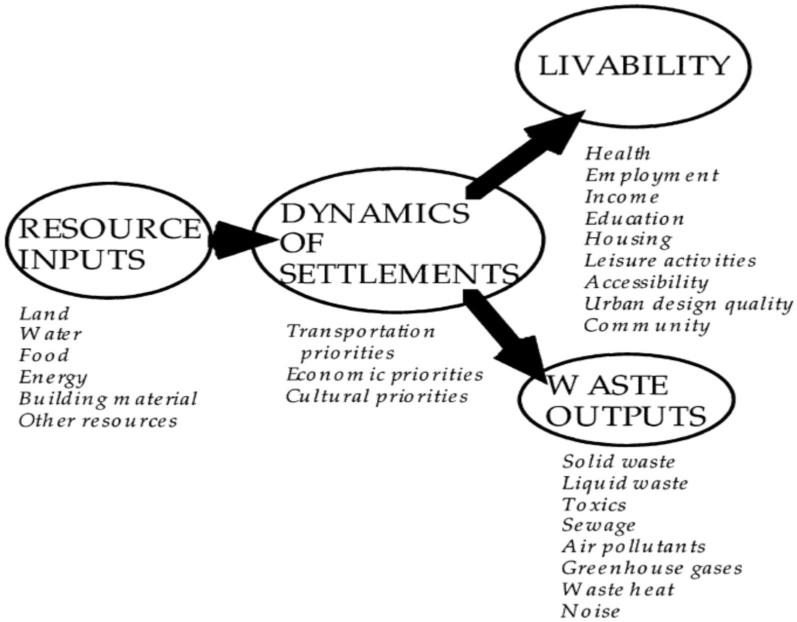


Figure 7: Extended Metabolism Model of Human Settlements (Source: Newman, 1999)

An important message from metabolism models and sustainability discussions is that the most effective way to reduce the potential negative impact caused by output wastes on the living environment is to reduce resource inputs. Many components in the Newman extended model (Newman, 1999) are closely related to the way planners conceptualize how cities grow and expand through complex interactions among different systems.

In general, such systems include natural environment systems and human-built systems as shown in Figure 8. In human-built systems, many urban components, such as the layout of transportation systems, buildings, and infrastructure systems, tend to be affected by land use types. Typically, different urban growth patterns and land use policies form different community resource consumptions and waste production portfolios. Land use patterns, the natural environment, the built environment, and the economic growth accompanied with population-employment influx are dynamically intertwined.

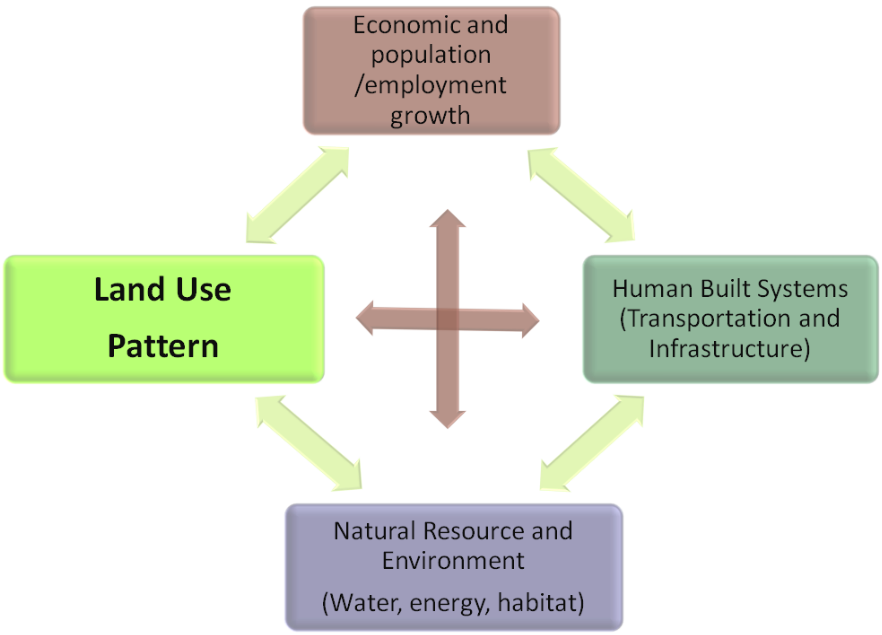


Figure 8: Conceptual Diagram of Interactions between Land use Patterns and Urban Systems

Economic growth leads to population and employment growth in cities. Such growth requires increased inputs of water, energy, and raw materials to construct commercial buildings, residential housing, and infrastructure systems, which conversely affect current and future land use patterns and spatial patterns of human activities. Within these dynamic interactions, different land use patterns would consequently result in different levels of natural resource inputs and waste outputs. This argument is similar to Newman's extended metabolism diagram.

URBAN WATER USE AND SECTORAL APPRACH

In order to estimate urban water demand, it is necessary to understand the components of customer types or end-use types. Typically, most public water supply systems provide water to multiple types of customers including single-family residences, multi-family residences, commercial businesses, industrial establishments, and institutional customers (Figure 9).

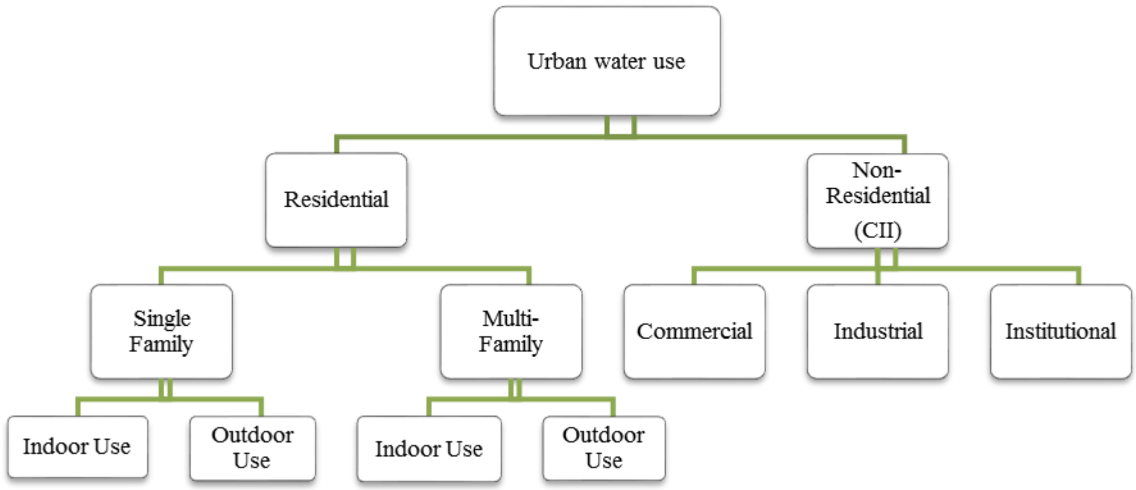


Figure 9. Structure of Urban Water Use (Illustrated by Author, Sources: Vickers, 2001 and MNGWPD, 2003)

In general, water-use sectors of single-family residences and multi-family residences are categorized as residential uses. Non-residential uses include commercial, industrial, and institutional (CII, hereafter) water uses. Residential customers consume 50 percent to 60 percent of total water production or sales in many communities across North America (Billings and Jones 2008). In 1995 according to the USGS, non-residential sector water use was reported as 17 percent for commercial use, 12 percent for industrial use, and 15 percent for public use and losses from public supplies across the U.S. (Solley, Pierce et al. 1998).

Depending on customer types and end-use behavior/purpose, end-use types can be categorized by indoor/outdoor use, or by water device types such as toilets, bath and kitchen, water appliances, and other uses including leaks. The breakdown of urban water use in Figure 9 is widely adoptable when local water management authorities or utility providers devise a variety of urban water demand models and conservation policies, considering the impact on water use across different customer types or end-use types.

FORECASTING URBAN WATER DEMAND

Water demand forecasting models and methods have been consistently discussed in literature for decades, and many different types of models and methods have been developed. These models and methods are unit water demand analysis (Brekke, Larsen et al. 2002), stochastic process models with time series data (Billings and Jones 2008), univariate time series analysis (Gardiner 1990), time series regression models (Polebitski and Palmer 2010), artificial neural networks (ANN) (Adamowski and Karapataki 2010), composite models or hybrid approach (Caiado 2009, Wang, Sun et al. 2009), and scenario-based approaches and decision support systems (DSS) (Feng, Li et al. 2007, Mohamed and Al-Mualla 2010, Polebitski, Palmer et al. 2010).

Other types of models are the time-series models that project historical water use trends into the future using a variety of techniques such as simple time trends, exponential smoothing and the Box-Jenkins (autoregressive integrated moving-average) models (Box and Pierce 1970, Box, Jenkins et al. 1994). In the same vein, regression models embrace socioeconomic factors influencing water use, and recent advances in developing structural forecast models include nonparametric forecasting models that adopt neural networks (Ghiassi, Zimbra et al. 2008) and fuzzy logic systems (Altunkaynak, Özger et al. 2005, Ghiassi, Zimbra et al. 2008).

According to Donkor et al. (2014), water demand forecasting methods and models differ depending on the forecast variables, the periodicity, which can range from hourly to annually, and the forecasting horizons categorized in either medium and long-term or short-term (Donkor, Mazzuchi et al. 2012). The end-use unit-based or sectoral approach is used for many water utility suppliers for mid- or long-term demand forecasts, whereas statistical models or regression models or neural network models are widely adopted in short-term or medium-term forecasts for optimization and peak-use estimation. In general, statistical models or regression models are widely adopted to estimate water demand using a series of socio-economic variables describing water consumers, as well as spatially explicit explanatory variables to capture the urban form and local development configuration characteristics.

The sectoral approach is an intuitive method in forecasting long-term water demand because total consumption for each sector can be calculated when the number of customers and the representative water use rates are known. The term is also similar to the ‘unit water demand analysis approach’ (Brekke, Larsen et al. 2002, Billings and Jones 2008). In this method, customer categories or water devices are disaggregated, and water demand is calculated by multiplication of per capita use of customer classes and the number of population or size of customers. In this mathematical expression, this approach can be expresses as in the Equation 1.

Equation 1. Unit Water Demand Analysis Approach (Brekke, 2002; Donkor et al 2012)

$$\boldsymbol{Q_t = \sum_{i=1}^{n} \beta_{i,t} * N_{i,t}}$$

Where: Q_t = total water use in given future time period t

$\beta_{i,t}$ = water use coefficient of sector in in time period in t

$N_{i,t}$ = size of water consumer in sector i in time period in t

Although this method is not considered as complex or sophisticated as other statistical models and non-parametric neural network models, it is the simplest approach used by many utilities in practice (Donkor, Mazzuchi et al. 2012). An example of the applying unit coefficient approach in demand forecast at metropolitan level is discussed by Hagen et al. for Washington metropolitan area (Hagen, Holmes et al. 2005). They argue that the method is thought be adequate "to provide the right balance between data needs and accuracy" and it is "transparent and easily understandable" so that multiple jurisdictions can apply it (Hagen, Holmes et al. 2005). When this approach is adopted for demand forecasting, unit water-use coefficients by different land use categories, such as residential, commercial, industrial and institutional (or public), should be applied separately in the forecasting process because the magnitude of water consumption varies by water customer types (Hagen, Holmes et al. 2005). This approach also is useful for measuring the potential water savings by specific conservation policies, or the technological improvement associated with (a) particular water use device(s).

One of the most widely adopted demand-forecasting applications taking the sectoral approach was the IWR-MAIN (Howe and Linaweaver 1967), developed by the U.S. Army Corps of Engineers Institute for Water Resources. The IWR-MAIN was used by many water utility providers in large metropolitan areas or cities, including the Indianapolis Water (27 sub-districts) , Phoenix Water Services department (four study areas), Metropolitan Water District of Southern California (57 study areas), Binghamton, New York, and the Southwest Florida Water Management district (62 study areas) (Opitz, Langowski et al. 1989, Baumann, Boland et al. 1998). The water demand and forecast module in the IWR-MAIN disaggregates the total urban water use into sectorial components; demands are calculated as products of the average rate of water use (e.g., per household or per employee) determined by a set of explanatory variables and the number of the users, such as the number of residents or employees (Dziegielewski and Boland 1989).

Using regression models, the IWR-MAIN estimates residential sector average water rates for seven subsectors (single-family, multi-family low-density, multi-family high-density, mobile homes, non-urban, use-added, and total residential). For the non-residential subsectors**,** the IWR-MAIN empirically estimates the CII (commercial/ industrial/ institutional) sector's water use. The classification of CII sectors in the IWR-MAIN follows the Standard Industrial Classification (SIC, hereafter) codes (Opitz, Langowski et al. 1989) from the U.S. Department of Commerce, which are composed of eight major industry groups, construction, manufacturing, transportation-communication-utilities (TCU, hereafter), wholesale trade, retail trade, finance-insurance-real estate (FIRE, hereafter), services, and public administration. Despite the availability of the theoretical models in the IWR-MAIN, the econometric models with the model elasticities for explanatory variables are not well defined; hence, the default calculation is expressed as the simple multiplication of the number of gallons per employee per day coefficient for the SIC categories with the number of employees (Dziegielewski and Boland 1989). Table 2 shows the example of the daily water use coefficient, gallons per employment per day (GED, thereafter) by the SIC codes. As employment data based on places of work are available from the U.S. Census Bureau (USCB), the water use for employment sectors can be easily calculated by using these coefficients.

Table 2: CII Sector Water Use GED Coefficients (Dziegieleswski and Boland 1989)

Group	SIC codes	Water use coefficient (gallons/employee/day)
Construction	15-17	20.7
Manufacturing	20-39	132.5
Transportation, communication, and utilities (TCU)	40-49	49.3
Wholesale trade	50-51	42.8
Retail Trade	52-59	93.1
Finance, insurance, real estate (FIRE)	60-67	70.8
Services	70-89	137.5
Public administration	91-97	105.7

DEFINITION OF SUSTAINABLE WATER USE IN LITERATURE

The definition of sustainable water use has been discussed in a way similar to the concept of ‘sustainability’(WECD 1987). Gleick (1995) has offered the definition of ‘sustainable water use’ as “the use of water that supports the ability of human society to endure and flourish into the indefinite future without undermining the integrity of the hydrological cycle or the ecological systems that depend on it” (Gleick 1995). Gleick (1998) later has elaborated on the definition by suggesting certain criteria for measuring sustainability as following: a sufficient level of water quantity should be guaranteed to maintain human health and health eco-system; water quality should be maintained to meet certain minimum standard; human actions in the long-run should not impair the renewability of water stock and flow; institute mechanisms and water planning decision-making should be democratic (Gleick 1998).

Kotas (2008) has also described the sustainable use of water as “the pattern of use which ensures satisfaction of needs for both the present and future generations” (Kostas 2008). In general, the definitions of sustainability emphasize inter-generational allocation of natural resources (Solow 1986) and focus on the limits of water use within the natural regeneration rate (Gleik 1998). Bithas (2008) expanded the definition of sustainable water use from an economic perspective, referring to ‘the avoidance of losing social welfare in the use of water’(Bithas 2008). While examining the importance of full-cost pricing and social equity issues, he has argued that efficient use of water is one of the necessary conditions to achieve sustainability (Bithas 2008).

GAPS IN LITERATURE: THE DEFINITION OF SUSTAINABLE WATER USE IN THIS DISSERTATION STUDY

While discussing the urban water use and sustainability and the forecasting methods, this study found the gaps in the literature that illustrate how land use change and urban growth policy would be linked to sustainable water use management plans. Despite a wide range of empirical and theoretical work on the estimation of urban water demand, not many studies have identified the explicit links between urban water use and urban land use planning (EPA 2006, Shandas and Hossein Parandvash 2010). Many studies have discussed how land use planning policies impact water quality (Zellner 2007) or urban flooding (Holway and Burby 1993); however, the consideration of land use planning as a nexus to water quantity or water consumption has not been widely discussed yet.

Based on the motivation to connect land use planning and water use, the definition statement of sustainable water use (and planning) in this dissertation study is refined as follows:.

Sustainable urban water use planning is in this dissertation study is: 'all planning efforts to promote sustainable urban development configuration and conservation actions that minimize the costs within the water use cycle (withdrawal-transfer-supply-waste water treatment) in urban areas while maximizing the benefit for maintaining healthy natural water resource system'. While water efficiency improvement through technology innovation can promote the reduction of water demand, a more sustainable growth policy and compact urban form would also not only reduce per capita water demand but also minimize the cost burden for new water supply-waste water management systems in urban areas. A reduction in water demand allows avoiding both unnecessary water withdrawal and the excessive short-term usage of water while securing water use to maintain urban economic growth. Also, a reduction in water demand allows human settlement to avoid greater damage to the surrounding local ecological and natural hydrologic systems.

DEFINITION OF CONSERVATION AND ESTIMATING CONSERVATION SAVINGS

Conservation is often referred to the least–cost method of accommodating the demands of a growing community (Billings and Jones 2008). Gleick et al. (2003) defined water conservation as "reducing water use by improving the efficiency of various uses of water, without decreasing services….or any action or technology that increases the productivity of water use” (Gleick, Haasz et al. 2003). They examined two types of conservation measures: ‘improving water use efficiency’ and ‘substituting reclaimed water for some end uses’(Gleick, Haasz et al. 2003). The former refers to the reduction of water demand without sacrificing functions or goals of water use. The latter refers to the reduction of water demand which was originally supplied by public water supply systems, but can be substituted by reclaimed water such as rainwater harvesting for some end-use like watering outdoor lawn (Gleick, Haasz et al. 2003). Vickers (2008) also defines water conservation as the “beneficial reduction in water loss, water or use”, and water efficiency as “minimization of the amount of water used to accomplish a function, task or results” (Vickers 2008). Baumann et al. (1980) defined water conservation as “the socially beneficial reduction of water use or water loss” in terms of cost-benefit approach (Baumann, Boland et al. 1980).

According to Billing and Jones (2008), the goals of a conservation program commonly aims to prevent water use from exceeding a historically observed normal use level, to prepare for drought, and, most importantly, to bring actively about a specified reduction in existing water use patterns and the rate of growth of water demands (Billings and Jones 2008). They have explained that successful long-term conservation can keep or decrease current water use demands, even as regional rapidly increasing population, employment, and economic activity is expected to increase (Billings and Jones 2008). They also have suggested that conservation can keep water rates stable or prevent a substantial increase of water rates from where there is the need for additional supplies of water and the expansion of water supply treatments, transmissions, and wastewater treatment facilities.

In this dissertation study, conservation in sustainable water use mainly refers to the reduction of water demand within an urban water system by both water efficiency improvement and an application of reclaimed water such as rainwater harvesting (RWH, hereafter).

Residential end use and conservation

Evaluating the savings potential of water-conservation options begins with understanding present water-use patterns and baseline usage. When the volume of water use by sectors and potential savings by efficiency measure is known, the maximum potential of water saving can be calculated.

Conservation programs targeting activities using larger percentages of total water offer the best opportunities for water savings (Billings and Jones 2008). The residential sector is the largest urban water use sector. Typical daily residential indoor water use is 69.3 gallons per capita. Figure 10 presents residential water share by different end-use types in the U.S.: toilets (26.7 percent), washers (21.7 percent), showers (16.8 percent), faucets (15.7 percent), leakages (13.7 percent), bath (1.7 percent), and others (3.6 percent) (Mayer, DeOreo et al. 1999).

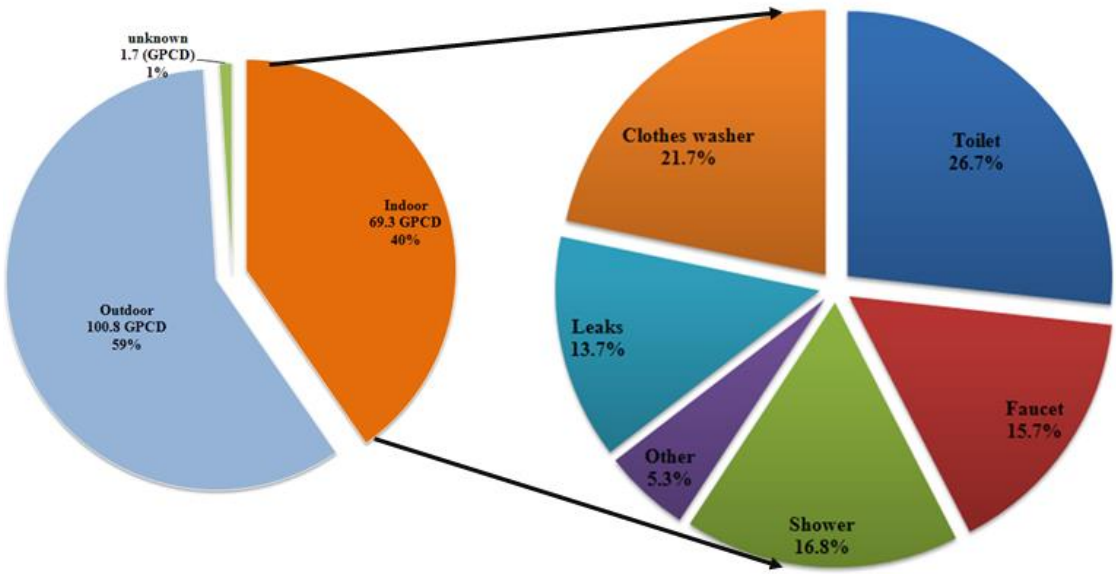


Figure 10. Residential Water use (Mean daily per capita) from 12 study sites in the U.S. (Mayer et al. 1999, AWWR study)

Many conservation studies, especially single-family residential water use studies, have discussed the estimates of water saving potential and estimated long-term conservation impacts. Vickers (2001) have suggested that water-efficient fixtures for indoor water devices for residential uses can reduce daily per-capita water use from 69.3 gallons to 45.3 gallons (34 percent decrease). It was assumed that pre-1980 model toilets, designed to use between 3.5 to 5.0 GPF (gallons per flush) would be replaced with low-flow 1.6 GPF toilets.

More recent standards for residential indoor use conservation have been published by the EPA (EPA 2009). According to the EPA's 'WaterSense Single-Family New Home Specification' (2009), the typical daily per capita water use for a single-family home can be reduced from 49.8 GPCD to 39.5 GPCD (gallons per capita day) (20.7percent decrease) when the new WaterSense standards are enforced. When comparing two studies, however, it should be noted that the efficient fixture standards in

Vickers's 2001 study were older standards and more efficient technologies and appliances become available since then. Therefore, the GPCD values in EPA's WaterSense study are typically lower than in Vickers's study.

In residential outdoor use, proper management of landscape water use and minimizing evaporation of outdoor pools are effective conservation actions; however, satisfactory or consistent estimates of outdoor residential water use are rarely found. A few studies quantify the effects of proper management on landscape. Western Policy Research (1997) found the combined effects of irrigation scheduling and proper system maintenance reduce water use by 20 percent (Research 1997). In another study in North Marin Water District in California, it was found that the proper choice of plants and careful landscape design (xeriscaping) could reduce water use by up to 54 percent (Nelson 1994). More recent study by Sovocool (2005) suggests that xeriscaping, compared to water use for turf grass, can save 55.8 gallons per square foot annually or 1.5 gallons per square feet at a minimum during the winter months and 9.6 gallons per square feet at a maximum during the summer months (Sovocool 2005). Table 3 summarizes the results of these studies associated with the anticipated water savings by device or program for residential use.

Table 3: Water Savings by Device or Programs (Mayer et al 1999, Maddaus and Maddaus, 2006, Vickers 2001, and EPA 2009)

		Source: Amy Vickers (2001)			Source: EPA (2009)			
		Non-conservation	Water-efficient fix	Expected Water Savings	Standard Use	Water Sense Expected Use	Expected Water Savings	
	Features	Daily gallons per capita (gpcd)	Daily gallons per capita (gpcd)	Daily gallons per capita (gpcd)	Daily gallons per capita (gpcd)	Daily gallons per capita (gpcd)	Daily gallons per capita (gpcd)	Percent
Indoor	Toilets	18.5	8.2	10.3	8.2	6.5	1.6	20%
	Bath and Faucets	12.1	10.8	1.3	11.3	10.7	0.6	4.8%
	Showers	11.6	10	1.6	9.9	9.9	0	0%
	Clothes Washers	15	10	5	15.5	8.6	7	45%
	Dishwashers	1	0.7	0.3	1.1	0.7	0.4	33%
	Hot water delivery systems	.	.		3.9	3.1	0.8	20%
	Leaks	9.5	4	5.5	.	.	.	
	Other Domestic Uses	1.6	1.6	0	.	.	.	
	Total Indoor	69.3	45.3	24	49.8	39.5	10.3	20.7 %
Outdoor	Xeriscaping	- Proper landscape design and xeriscaping can reduce outdoor water use up to 54 percent (Nelson, 1994) - Comparing turf grass, xeriscaping can save 55.8 gallons per square foot annually (1.5 gallons/sq.ft. as min. in winter, 9.6 gallons/sq.ft. at max, in summer) (Sovocool, 2005)						
	Rain sensor	- 10 GPCD can be saved by rain sensor						
	Effective land scape strategies	- Effective landscaping can save up to 50% of outdoor water use for landscaping (Source: The Saving Water Partnership "Water Efficient Irrigation Study: Final Report. May 2003)						

Non-residential sector end use and conservation

Non-residential or commonly referring to commercial-industrial-institutional (CII, hereafter) water use estimates vary widely depending on the demographics of the utility and the way CII sectors are defined (Morales, Heaney et al. 2011). The difficulty in estimating current CII water use and identifying potential savings in the sectors is due to limited availability of various types of customer information, device inventories, poorly standardized data format, and wide variations of quantity of water use among the mix of end uses. However, several studies and local/regional water councils have published overviews of CII water use and efficiency measures. Dziegielewski et al. (2000) discussed the characteristics of commercial and institutional water uses (Dziegielewski 2000). The EPA's Water Efficiency in the Commercial and Institutional Sector (WaterSense 2009) can be applied to the industrial use sector despite a lack of subsector-specific data (e.g., water use by facility and end use). Other studies regarding CII water use include Colorado's Water Wise study (The Brendle Group 2007), which discussed the CII sectors conservation benchmarks, 'Water efficiency manual for CII facilities' by the North Carolina Department of Environment and Natural resources (Cohen, Ortez et al. 2009), and 'A water conservation guide for CII Users' by the New Mexico Office of the State Engineer (1999).

The saving ranges from many conservation studies are useful guidelines for planners when setting a conservation scenario. The California Department Water Resources and the EPA completed the water audits at 741 commercial sites in six states and found that potential water savings from efficiency measures ranged from 20 percent to 26 percent (Vickers 2001). Another study, with 902 commercial and industrial (CI) facilities in the Metropolitan Water District of Southern California, has suggested that estimated average potential water savings can be 29 percent, with high opportunities in domestic plumbing fixtures, industrial processes, and landscape irrigation (Sweeten and Chaput 1997). The survey report (Dziegielewski, Kiefer et al. 2000) from the AWWA research foundation have estimated potential savings are within 15 to 50 percent range, with 15 to 35 percent being typical when implementing the CI conservation programs (Vickers 2001).

Gleick et al. (2003) have analyzed California's urban water use and potential savings in 2000 to provide a comprehensive overview for urban water use including CII end uses (Gleick, Haasz et al. 2003). In their work landscaping (35%) is the largest source of water demand in the CII sectors, followed by process (17 percent), restroom (16 percent), and cooling (15 percent) (Figure 11). This study has suggested that landscaping and plumbing fixtures in commercial uses are most effective targets for conservation in commercial uses in CII sector (Gleick 2003)

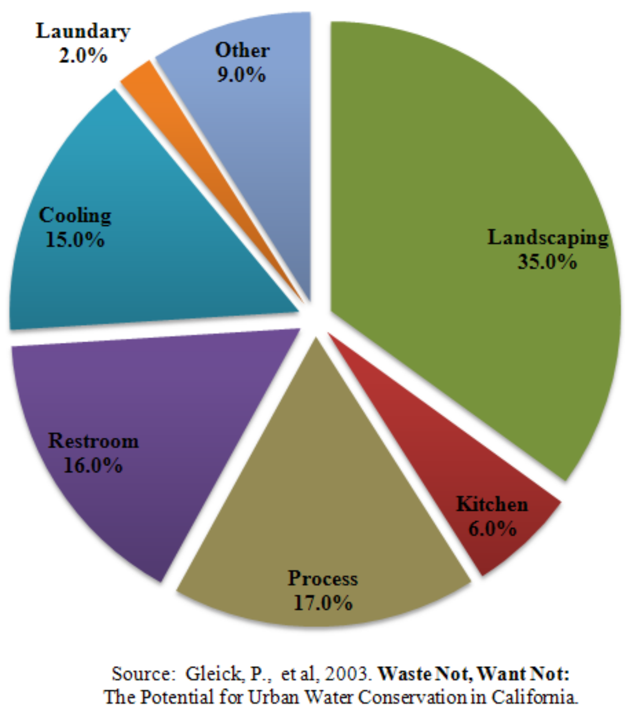


Figure 11. Estimated Water Use in the CII Sectors by End Use (Gleick, p. et al. 2003)

Rainwater Harvesting (RWH) as a Conservation Option

Rainwater is considered to be water sources for the irrigation of farm land, irrigation of gardens, flushing toilets, cleaning of road and outdoor surfaces, and other non-potable uses (Boers and Ben-Asher 1982, Nolde 2007). Rainwater harvesting (RWH, hereafter) is one of many conservation options that potentially provides access to a reclaimed water source, although many potential possibilities of collecting and using rainwater have been frequently been ignored (Angrill, Farreny et al. 2012). Until 2007 there were about 250,000 RWH systems in use in the United States (KInkade-Levario 2007); Texas, Virginia, Oregon, the State of Washington, and other states have developed guidelines for designing and installing RWH systems. But RHW is still an underutilized tool, mainly due to logistical problems, such as cistern locations, changes in facility use, and poor public perception of the harvested rainwater (Jones and Hunt 2010).

Angrill et al (2002) have examined the environmental impacts of RWH in terms of infrastructure associated with the two layouts of residential urban density, 'compact city model' and 'diffuse urban city model' (Angrill, Farreny et al. 2012). They found that the compact city model with a higher density would result in lower negative environmental impacts and higher water efficiencies with 47 percent of the demand met (Angrill, Farreny et al. 2012). They concluded that "a priori" rain water can be a competitive resource in urban areas with scare water resources. Chilton et al. (2000) have studied the collection efficiency and the system applicability of commercial buildings (supermarkets) with large roofs in London, England during an 8-month period (Chilton, Maidment et al. 2000). They found that 53.9 percent (January–June 1998) and 48.1 percent (July–November 1998) of actual collection efficiencies were achieved in a prototype system, and depending on persistent or heavy rain, 20.9 percent or 28.6 percent of the average demand was satisfied.

SUSTAINABLE URBAN WATER USE PLANNING AND URBAN DEVELOPMENT CONFIGURATION APPROACH

DRIVERS OF URBAN WATER USE

Water use is fundamentally linked to economic and societal growth and its well-being (Franczyk and Chang 2009). A wide range of studies and practical evidences suggests that water demand is affected by many socio-economic variables, weather and climate variables, and local water pricing and conservation policies. Common socio-economic variables include population growth, one of the most important determinants of water use (Ruth, Bernier et al. 2007), economic growth (Gleick 2003), price of water (Agthe and Billings 2002, Arbués, García-Valiñas et al. 2003), and household income (Syme, Shao et al. 2004, Domene and Saurí 2006, Balling and Cubaque 2009). Gleick (2003) assumes that population and economic growth lead to increases in water withdrawals and supply infrastructure expansion (Gleick 2003). Increase in population and employment usually produce new developments in the urban areas, which require additional water use for drinking, irrigation, industrial use, hydroelectric power production, transportation, and recreational purposes.

A snapshot of water use published by the United States Geological Survey (Kenny, Barber et al. 2009, USGS 2009) shows that many populated states, especially in the South and the West where increased population trends were shown for the last several decades, had high levels of total water withdrawals from surface and ground water sources (Figure 12) .

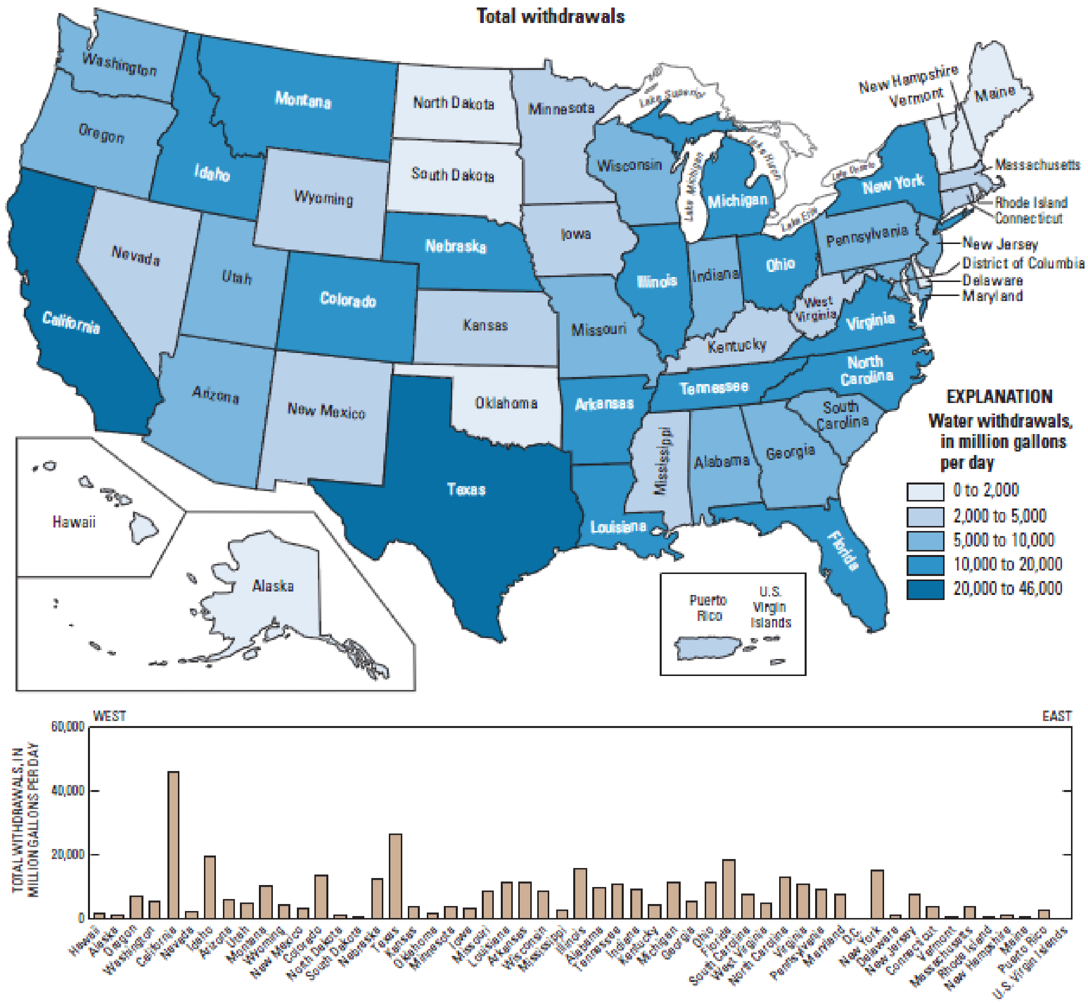


Figure 12: Total Withdrawals of Surface and Ground Water in 2005 (Kenny, Barber et al. 2009)

Another reason why the South and the West regions have a high level of withdrawal is related to weather and climate variability. Weather and climate variables such as temperature, precipitation (Balling Jr and Gober 2007, Franczyk and Chang 2009), and evapotranspiration (ET) (Zhou, McMahon et al. 2002) were discussed as important variables related to weather and climate variability. Balling et al. (2008) also discussed the sensitivity of residential water consumption primarily because outdoor use is substantially affected by climate variability (Balling, Gober et al. 2008). Seasonal components such as maximum summer temperatures and precipitations are also strongly associated with seasonal water use (Polebitski and Palmer 2010). Hot and dry weather and climate variability also affect outdoor water use because of the existence of pools (Domene and Saurí 2006, Wentz and Gober 2007) and high evapotranspiration rates during lawn watering (Syme, Shao et al. 2004, Fox, McIntosh et al. 2009)

In the literature of water demand models, household income and the price of water are discussed extensively. Domene and Sauri (2006) investigated the relationship between urbanization trends and residential water consumption in metropolitan Barcelona and found that household income is a significant predictor of water use (Domene and Saurí 2006). Balling et al. (2007) also found that a high proportion of high-income residents would be an explanatory factor for spatial water consumption patterns (Balling Jr and Gober 2007). According to Arbues et al. (2003), water pricing is an important variable in explaining the quantity of water use at the household level. In regional spatial scale, Sohn (2011) found that the quantity of water use in cities and counties in the Southeastern U.S. was significantly correlated to the water price (Sohn 2011). In economics standpoint, water pricing, household income, and the quantity of water use would be influenced by each other; hence, water pricing policy is one of favored conservation actions by many water management authorities and water utilities. However, nonlinear and discontinuity of the price structure introduces difficulties in specifying economic models and demand modeling (House-Peters and Chang 2011).

Gerrity and Snyder (2011) conducted a study at the metropolitan scale. Their discussion of the various reasons of water withdrawals associated with Gross Metropolitan Product (GMP), income, and employment is buttressed by their investigation of water withdrawal in the 32 most populous metropolitan areas using the U.S. water withdrawal data for 2005 (Kenny, Barber et al. 2009). They conclude that the ratio of GMP to the water withdrawals (GMP/H_2O) metric can be useful to understand water use in metropolitan areas, but it is less applicable for regional analysis due to the unique aspects of water resource portfolios and the local economies.

SPATIALLY EXPLICIT VARIABLES ON URBAN WATER USE

An important recent trend in investigating water use determinants and demand modeling is to examine the variables and demand analyses that are associated with the spatial pattern (House-Peters and Chang 2011). Spatially explicit variables usually refer to the explanatory variables associated with physical and structural characteristics of the built environment. They are typically variation of lot size, lawn, and pools or derived variables from urban settlement types, such as density and percentage of single-family housing.

There is a wide discussion about the many different types of spatially explicit variables such as housing type (Troy and Holloway 2004), housing typology (Fox, McIntosh et al. 2009), proportion of single-family households (Chang, Shandas et al. 2010), lot size or property size (Renwick and Green 2000, Balling, Gober et al. 2008), property values as a proxy for household income (Howe and Linaweaver 1967, Dandy, Nguyen et al. 1997), size of the outdoor space (House-Peters, Pratt et al. 2010), house square footage (Chang, Parandvash et al. 2010), existence of a garden (Domene and Saurí 2006), pools (Guhathakurta and Gober 2007, Balling, Gober et al. 2008), NDVI (normalized difference of vegetation index) (Wentz and Gober 2007), or the urban heat island (UHI) effect (Guhathakurta and Gober 2007).

More recently, spatial patterns of urban water use in the context of regional scale have been discussed by Sohn (2011). He combined four mutually exclusive water uses—public supply, domestic/residential, industrial, and thermoelectric power(Hutson 2004)—and conducted spatial analyses to identify trends of urban water use in the southeastern U.S. The analyses conclude that counties with large quantities of water use are spatially clustered (Sohn 2011)

URBAN GROWTH, SPRAWL AND WATER USE

Sprawl is frequently described as a spatial pattern of contemporary development commonly occurring beyond the edge of developed urban areas. The definitions of sprawl are discussed in many reports and studies focusing on land use change patterns, excessive transportation commuting costs, or impacts on environmental quality (Burchell 2003, Ewing 2008, Stone Jr 2008).

Households in areas of suburban sprawl may consume more water than those who live in denser cities due to several reasons. First, in terms of the magnitude of water consumption, sprawl and low-density development increase water demand in residential areas mainly due to large lot sizes and acres of turf grass, a large household, or outdoor pools (Wentz and Gober 2007). House-Peters et al. (2010) discussed spatial concentrations of water use with large lot sizes and affluence characteristics such as property value. They found that household size affected indoor water use and the size of the property affected seasonal outdoor water use (House-Peters, Pratt et al. 2010).

Second, rapidly increasing new water demands would likely to be dispersed all across suburban and rural areas because most new development occur at fringe of urban areas. New developments with low densities in suburban and rural areas, coupled with segregated land uses, tend to spur new residential and employment water demands in the suburban area. Figure 13 represents how sprawl and low-density development would affect overall water demand in various perspectives.

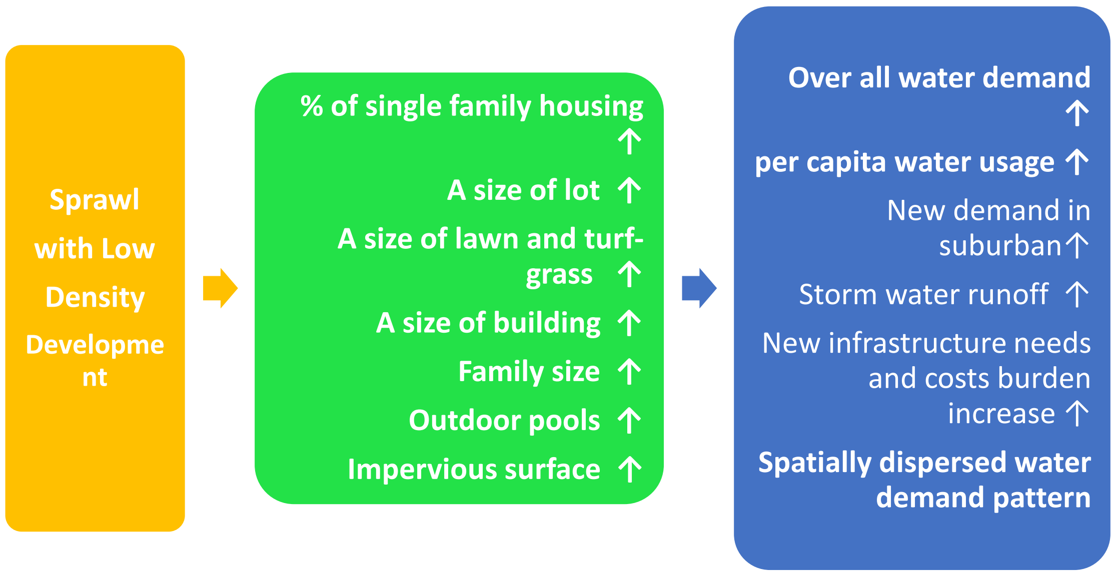


Figure 13: Impact of Sprawl on Urban Water Use

Sprawl is also prone to elevated urban service costs – especially infrastructure-intensive services such as roads, water lines, and sewer lines due to spatial dispersion (Downing and Gustely 1977, Burchell and Listokin 1995). Burchell et al (2002) estimated the total water and sewer infrastructure costs savings between uncontrolled growth (sprawl) and controlled growth over 25 years (from 2000 to 2025) in the U.S. as to $ 12.6 billion dollars (Burchell, Lowenstein et al. 2002) (Table 4). Especially, cost of savings switching from sprawl to the control growth scenario in South and West region were higher than the other two.

Speir and Stephenson (2002) investigate whether sprawl would increase the public water and sewer costs associated with alternative housing patterns in terms of lot size, tract dispersion, and distance from existing water and sewer service centers (Speir and Stephenson 2002). Duncan et al. (1989) and Frank (1989) also found that water and sewage costs for compact, contiguous housing patterns are 60 percent and 66 percent of those in spread-out patterns, respectively (Duncan 1989, Frank 1989). The results suggested that the more dispersed the housing patterns are, the higher cost to supply the area with public water and sewer services.

Table 4. Water and Sewer Infrastructure - Uncontrolled-and Controlled -Growth Scenarios (US and by Region: 2000 to 2025) (Burchell, et al, 2002, page 10. A Part of the Table)

Region	Total Infrastructure Costs		
	Uncontrolled Growth ($M)	Controlled Growth ($M)	Cost savings ($M)
Northeast	16,015	14,751	1,264
Midwest	30,393	28,839	1,556
South	84,573	79,026	5,547
West	58,786	54,544	4,242
United States	189,767	177,160	12,609

Low-density development and sprawl may impact negatively on local sustainable resource management and economic growth because they are costly. In order to discuss sustainable water resource management plans, planners or planning authorities need to understand what drives an increase of water demand and how water demand varies by different geographical locations and urban characteristics.

CHAPTER 3

COUNTY LEVEL ANALYSIS

This chapter explores the relationship between urban water use and explanatory factors associated with urban form and the built-environment characteristics, typically known as spatially explicit variables. It includes empirical analyses to examine the relationship between explanatory variables of interest and water use statistics at the county scale (County level analysis). In the County level analysis, urban form and land-use-related variables, such as population (urban) density, the percent of single-family units, percent of structure built since 1990, and climate variability are important explanatory factors in the research design. The resulting estimated coefficients and their signs, will illustrate the importance of the independent variables to per-capita daily water use.

GOAL OF SUTDY

This section endeavors to develop a cross-sectional analysis at the county level, using data provided by the U.S. Census. The major goal of this county-level analysis is to highlight the relationship between the variables associated with urban development configurations and urban water use. The major goal of the analysis is to identify the controlling urban form factors that local and regional water management planners and growth policy decision makers and analysts should focus on in order to promote water reduction.

RESEARCH DESIGN AND METHODS

To understand the influence of spatial variables on water use further, this study presents a cross-sectional county level analysis. The statistical regression models are designed at the county level across U.S. metropolitan areas. The county level analysis focuses on finding useful parameters of urban form and the urban built-environment characteristics that best explain variations of urban water use within and near the U.S. metropolitan areas. In the following Chapter 4, contrasting with the County level analysis, the Parcel-level analysis is designed to see whether annual water use would vary by lot size and property value, which is considered as a proxy of household income.

In general, the total volume of water use in any given county is greatly affected by two causal factors: (1) population size and (2) per capita water use. As urban growth occurs, population size increases. If a region aims to achieve water reduction given its population growth, the per capita water use rate has to be reduced. Therefore, this study pays attention to per capita water use rate as a dependent variable.

Various functional forms and the selection of the independent variables will be explored depending on the category of water demand in the regression model below.

Equation 2. Regression model for county level analysis

$$q_j = \alpha_0 + \beta_i X_{i,j} + \varepsilon_{i,j}$$

Where, q_j = per capita daily rate of water use in geographical area County j,

α_0 = *constant*, β_i = coefficient of explanatory variable X_i. $\varepsilon_{i,j}$: error terms

DATA COLLECTION AND PROCESSING

First, a list of 3,222 counties or county equivalents ("counties" hereafter) was gathered from the U.S. Census. Tabular data and geographic information systems (GIS, hereafter) county data and boundaries of metropolitan statistics area (MSA, hereafter) data (base year 2005) were collected and compiled into a GIS database.

Second, 1,744 counties in which US. Census American Community Survey (ACS) 3-year estimates from year 2005 to 2007 data of the variables of interest were available were identified. Although the 3-year estimate dataset contains information only for approximately half of the total counties in the U.S., most counties with valid estimates were matched with the counties within or near US metropolitan areas. In addition to the US Census 3-year estimates, the U.S. Census County Business Patterns (CBP) data and county-level web sites also provided data for variables of interest associated with county employment information, including total employees and industry classification.

Third, a list was created of the 1,590 counties near or inside metropolitan areas for which county climate variables, climate normals, were available. The dataset is obtained from U.S. National Climate Data Center, NOAA (National Oceanic and Atmospheric Administration). Climate variables are derived from climate normal[1] that are three decade averages of climatological variable including temperature and precipitation. Climate normals (for the time period 1981–2010) of annual temperature, annual precipitation, heating and cooling degree days (HDD and CDD hereafter), calculated from observations

1 This product is produced once every 10 years. The data is available at http://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/climate-normals

at approximately 9,800 stations operated by NOAA's National Weather Service are included in the dataset. Figure 14 shows the example of geographic distribution of climate monitoring stations in the state of Georgia.

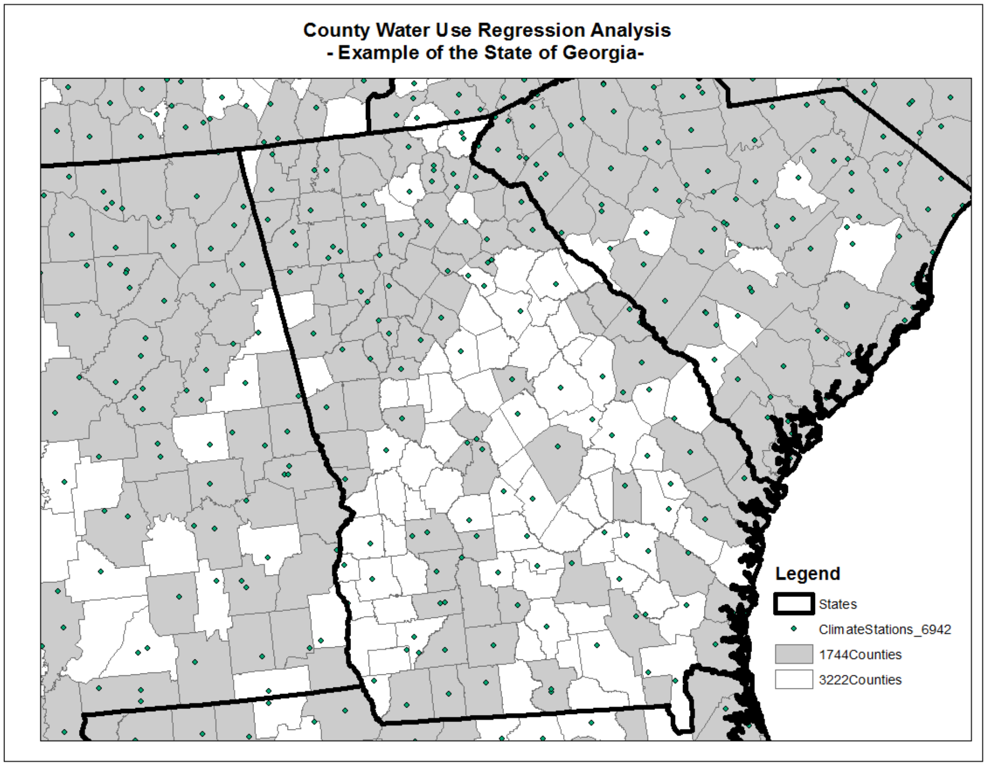


Figure 14: Distribution of Climate Monitoring Stations in the US: Example of Georgia (Source: US National Climate Data Center)

Figures 15 and 16 show the long term average temperature and annual precipitation 30 year normal in the US by county. Counties for which these climate variables were not available were removed from the selection process. For those counties with multiple climate monitoring stations, the average of observation values within the county is calculated and used as the climate normal.

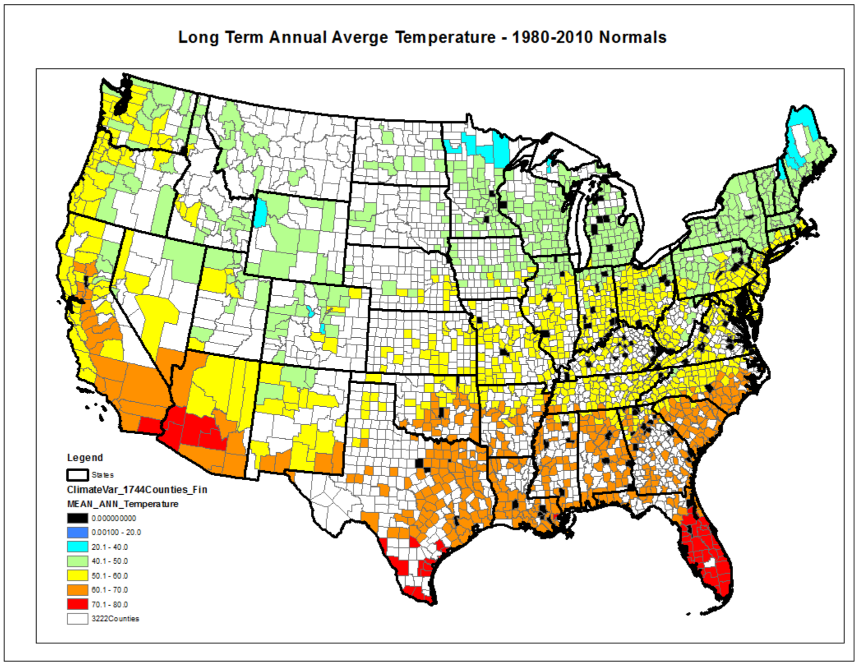


Figure 15: Long Term Annual Average Temperature in the U.S, 30 year (1980~2010) Normals (Source: US National Climate Data Center. The map is produced by the author)

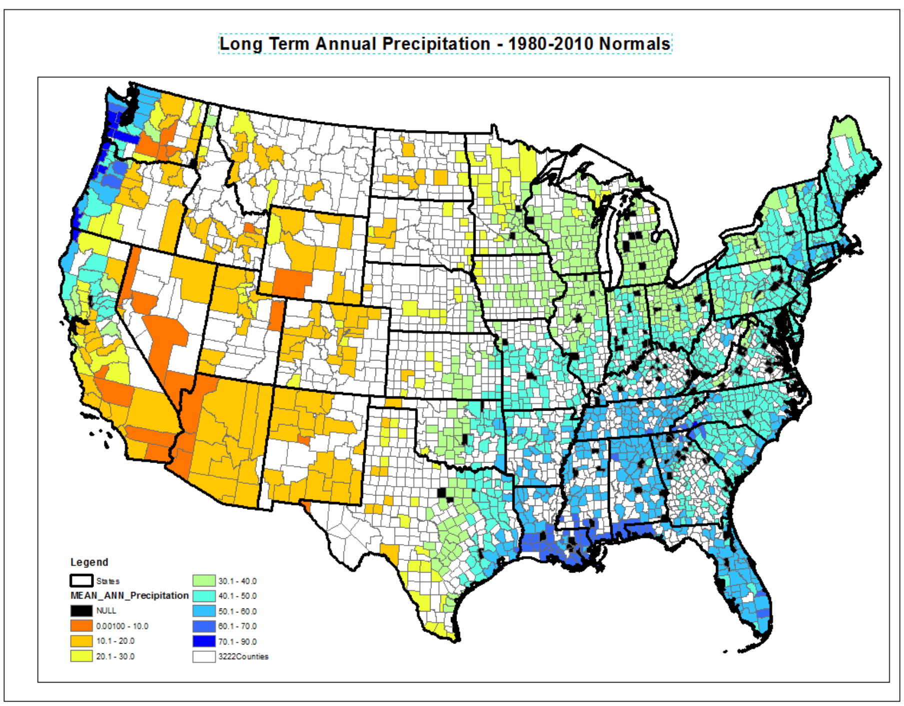


Figure 16: Long Term Annual Precipitation Totals in the U.S, 30 year (1980~2010) Normals (Source: US National Climate Data Center. The map is produced by the author))

Finally, water use data in the US at the county level in 2005 (Kenny, Barber et al. 2009) were collected and added to the county regression analysis database. Table 5 shows the summary of data collection process and the maps of selected counties in the US (Figure 17). The table also shows the number of counties within metropolitan areas and/or no electrical power thermals water withdrawals available that are used for the domestic water use analysis.

Table 5: County Selection Process

Selection Criteria	Dependent Variable in Regression	Number of Qualified Counties				
Counties or county equivalents	Total Water Use	*	*	*	*	*
US Census year 2005-2007 3 year estimates available			*	*	*	*
Counties with climate variables valid (temperature, precipitation, CDDs and HDDs)	Urban water use			*	*	*
Located within metropolitan areas					*	*
Located within metropolitan areas and no electrical power thermal water use	Domestic water use					*
Number of counties		3,222	1,744	1590	810	481

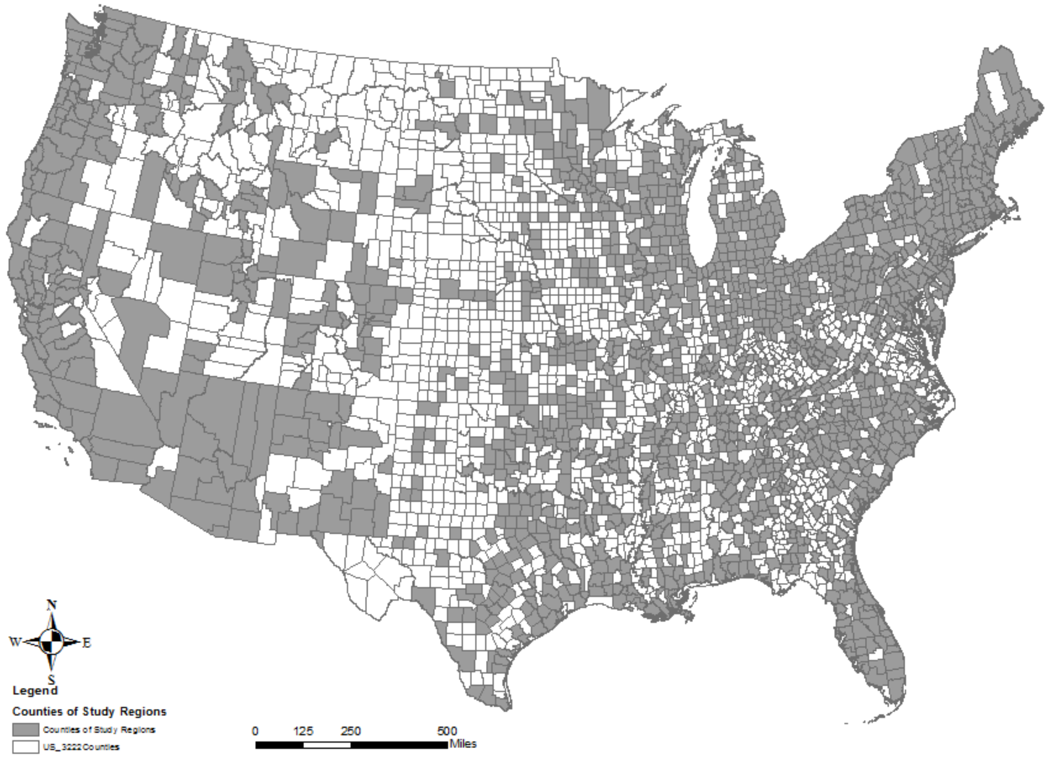


Figure 17: Selected counties in the study for county analysis (1590 counties)

<u>Selecting and processing variables of interest: Dependent variables-US water use at county data</u>

In literature most previous analyses were conducted at the local or regional level, making a national level analysis valuable. However, when developing a cross-sectional analysis of counties, comparable water-use data is limited. The water use or withdrawal data at county level across the entire United States is available from the U.S. Geological Survey ("The USGS", hereafter) water use report, "Estimated Use of Water in the US 2005" (Kenny, Barber et al. 2009). The USGS's National Water-Use Information Program is responsible for compiling and disseminating the nation's water-use data. The USGS works in cooperation with local, state, and federal environmental agencies to collect water-use information and then compiles these data to produce water-use information aggregated at the county, state, and national levels for every five years. The most recent water use data at the time of this research was for 2005, which was published and were available online in year 2009.

According to the USGS county water use survey data and the study report (Hutson et al. 2009), the total water use at county level is divided into a series of categories; (1) public supply, (2) self-supplied domestic, (3) industrial, (4) irrigation, (5) livestock, (6) aquaculture, (6) mining, and (7) thermoelectric power uses. Within these categories, the definition of water use categories related to urban water uses are as below.

- Public supply: water withdrawn by public and private water suppliers that furnish water to at least 25 people or have a minimum of 15 connections for public use.
- Domestic: water used for indoor and outdoor household purposes.
- Industrial: water used for such purposes as fabricating, processing, washing, diluting, cooling or transporting a product; incorporating water into a product; or for sanitation needs within the manufacturing facility.
- Thermoelectric power: water used in cooling when generating electricity with steam-driven turbine generators.

Finally, this study includes three types of daily per capita water use rate as dependent variables of interest: (1) daily per capita total water use rate, (2) daily per capita urban water use rate and (3) daily per capita domestic water use rate. In this dissertation study per capita water use rate refers to per day use unless specified differently. The per capita total water use rate is calculated from the summation of all volume of water in these categories divided by dividing the sum of total water use, across all categories, by county population. The per capita urban water use rate is also calculated in a similar way using county population; however, urban water use rate also divides by county population, but only includes four mutually exclusive water uses: public supply, domestic, industrial, and thermoelectric power use by definition. In the series of report, the water use categories and their definitions have been changed. Since 2005, USGS started to provide information on whether the volume of water use is self-supplied (water from wells or ground water) or provided through a public supply system. In order to avoid double counting the volume of water use in each category, the dataset was carefully examined. The total volume of urban water use by county is calculated as the summation of water volumes in public supply, self-supplied domestic, self-supplied industrial, and thermoelectric power use by county. Per capita urban water use rate is calculated by total urban water use divided by county population. In similar way, total volume of domestic water use is the summation of self-supplied domestic water and domestic water use through public supply. Per-capita domestic use rate is calculated as total volume of domestic water use divided by county population.

Selecting and processing variables of interest: Independent variables

The independent variables were selected through several iterative processes, on the basis of (1) literature review, (2) data availability, and (3) detected relationships among variables of interests. This study organizes the independent variables into several categories first: urban form or urban development configuration, demographic, and regional climate characteristics, and dummy variables. Then the variables are attributed to two groups, namely the policy variables and the background variables.

The policy variables refer to the variables most likely influenced by specific policy actions. Good examples of policy variables would be the percentage of single-family residential units (PSFH, hereafter) and the population density because planners can directly influence such land-use patterns through zoning changes and other policy tools.

The background variables refer to those less easily influenced by policy changes. Such examples are the climate variables (temperature and annual precipitation), the percent of structure built year since 1990, within or near metropolitan areas (MSAs), average house hold size, median incomes, and so forth.

The independent variables in the county analysis are listed below. The policy variables this study is interested in are marked with the '*' symbol.

a. Urban form or urban development configuration: Population density*, employment density*, the percent of single family housing units detached*, the percent of structures built since year 1990.
b. Demographic: median household income, average household size, total population, total employment, the number (or the percent) of employees in manufacturing sector (SIC-level 3), the number (or the percent) of employment in wholesale, retail sales, and warehousing (SIC-level 4), the number (or the percent) of employment in information, FIRE (finance and real-estate), and technology services (SIC-level 5), the number (the percent) of employment in education and health service (SIC-level 6),
c. Local climate characteristics: Long-term averages of annual average temperature, long-term averages of annual precipitation, Cooling degree days (CDD), Heating degree days (HDD)

d. Dummy control variables: within or near metropolitan area, excessive water withdrawal for thermoelectric power generation*

To finalize the list of independent variables of interest and to improve the design of regression analysis, this study developed a couple of strategies. First, the descriptive statistics and frequency distribution curve of observations were examined to see the skewness of distribution. If the curve was not close to normally distributed and skewed, the variable was transformed to the logarithm form in the regression analysis. Because the dependent variable in this analysis is log (*y*) form, the model is interpreted either *log-level* model (log (*y*) as dependent variable and *x* as independent variable) or *log-log* model (log (*y*) as dependent variable and log (*x*) as independent variable). In both cases, interpretation of coefficients b_1 is represented as the equations below (Wooldridge 2015).

Log-level model: $\% \Delta y = (100\, b_1)\, \Delta x$

Log-log model: $\% \Delta y = b_1\, \% \Delta x$

Second, when the absolute values were appropriate to represent the characteristics of the county, but high correlations among other variables threatens the validity of regression analysis, the percentage values of concerned variables instead of the absolute values were included. For example, total number of wholesale and retail sales (SIC-level 4) may a good predictor for per capita water use in county; however, it would be highly correlated to total employment; instead the percent of employment in wholesale and retail sales sector (SIC level 4) in the county is used in the analysis.

Third, the multicollinearity was examined by conducting a bivariate correlation analysis. As shown in Table 6, the results suggest that there are a couple of high correlations (with correlation values larger than 0.8) among several pairs of exploratory variables; population and employment, density of population and density of employment, average temperature and CDD-HDD. This multicollinearity threatens the validity of regression analysis. Such variables were thus removed or replaced with other variables in the same independent variable category when regression analysis is performed and tested.

Fourth, this study conducted test-and-trial regression analyses to identify a list of variables that result in high R-square and high t-statistics with the statistically significant coefficients. As a result, this study determined the final list of variables of interest in individual groups of variables as shown in Table 8. The correlation coefficients among the final selection of exploratory variables are presented in Table 7.

Table 6: Correlation Matrix of Variables of Interests

	Dependent 1: LN GPCD, total water withdrawl	**Dependent 2: LN GPCD, Urban water use**	**Dependent 3 : LN GPCD, Domestic total**	Percent of a single unit detached	percent of structure built since year 1990	Average household size	LN median HH income	LN Total population in county	LN Employment Total	LN population density, person/sqmile	LN employment density, employee/sqmile	Percent of lev 3 employment: manufacturing	Pecent of lev 4 employment: wholesales, retail sales, warehousing	Percent of lev 5 employment: information, FIRE, tech services	Percent of lev 6 employment: education and health service	LN Long-term averages of annual average temperature, 1980-2010 normals	LN Long-term averages of annual precipitation totals	LN Long-term averages of annual cooling degree days with base 65F, 1980-2010 normals	LN Long-term averages of annual heating degree days with base 65F, 1980-2010 normals	Dummy: Metro (0: Not metro 1: metro)	Dummy: Thermoelectric Power (0: No use for thermoelectric power, 1: Use for thermoelectric power)
LN GPCD, total water withdrawl	1																				
LN GPCD, Urban water use	.730**	1																			
LN GPCD, Domestic total	.360**	.140**	1																		
Percent of a single unit detached	.020	.009	-.105**	1																	
percent of structure built since year 1990	-.048	-.075**	.102**	-.009	1																
Average household size	.097**	-.004	.264**	-.047	.339**	1															
LN median HH income	-.048	.052*	-.035	.014	.234**	.191**	1														
LN Total population in county	-.061*	.135**	.017	-.414**	.052*	.180**	.484**	1													
LN Employment Total	-.062*	.136**	-.012	-.417**	-.006	.075**	.489**	.964**	1												
LN population density, person/sqmile	-.271**	.045	-.187**	-.364**	-.012	.054*	.418**	.800**	.799**	1											
LN employment density, employee/sqmile	-.244**	.058*	-.185**	-.378**	-.052*	-.019	.431**	.797**	.852**	.975**	1										
Percent of lev 3 employment: manufacturing	-.083**	-.015	-.234**	.283**	-.068**	-.058*	-.235**	-.344**	-.296**	-.154**	-.138**	1									
Pecent of lev 4 employment: wholesales, retail sales, warehousing	.108**	-.008	.111**	.071**	.092**	.178**	-.046	-.036	-.090**	-.118**	-.157**	-.309**	1								
Percent of lev 5 employment: information, FIRE, tech services	-.088**	.048	.035	-.369**	.065**	.040	.510**	.734**	.762**	.649**	.685**	-.458**	-.089**	1							
Percent of lev 6 employment: education and health service	-.048	-.014	-.068**	-.099**	-.350**	-.129**	-.252**	.059*	.040	.037	.021	-.318**	-.029	-.043	1						
LN Long-term averages of annual average temperature, 1980-2010 normals	.014	.058*	.248**	-.199**	.296**	.276**	-.256**	.126**	.055*	.170**	.108**	-.050*	.093**	.054*	-.086**	1					
LN Long-term averages of annual precipitation totals	-.335**	.004	-.317**	.010	.008	-.229**	-.126**	-.024	-.033	.289**	.239**	.190**	-.047	-.031	.022	.311**	1				
LN Long-term averages of annual cooling degree days with base 65F, 1980-2010 normals	-.036	.042	.112**	-.084**	.210**	.213**	-.238**	.074**	.033	.180**	.134**	.066**	.088**	.015	-.057*	.842**	.238**	1			
LN Long-term averages of annual heating degree days with base 65F, 1980-2010 normals	-.061*	-.086**	-.262**	.257**	-.280**	-.264**	.178**	-.176**	-.106**	-.145**	-.092**	.143**	-.110**	-.088**	.060*	-.896**	-.250**	-.704**	1		
Dummy: Metro (0: Not metro 1: metro)	-.075**	.104**	-.017	-.186**	.222**	.196**	.490**	.610**	.556**	.574**	.535**	-.258**	.004	.476**	-.035	.117**	.002	.116**	-.114**	1	
Dummy: Thermoelectric Power (0: No use for thermoelectic power, 1: Use for thermoelectric power)	.357**	.560**	-.011	-.146**	-.123**	-.013	.141**	.364**	.372**	.280**	.298**	-.138**	-.017	.248**	.059*	.031	-.020	.071**	-.075**	.217**	1

Table 7: Correlation Matrix of Variables of Interests: After Removal of Multicollinearity Issue

	Percent of a single unit detached	percent of structure built since year 1990	Average household size	LN median HH income	LN population density, person/sqmile	Percent of lev 3 employment: manufacturing	Pecent of lev 4 employment: wholesales, retail sales, warehousing	Percent of lev 5 employment: information, FIRE, tech services	Percent of lev 6 employment: education and health service	LN Long-term averages of annual average temperature, 1980-2010 normals	LN Long-term averages of annual precipitation totals	Dummy: Metro (0: Not metro 1: metro)	Dummy: Thermoelectric Power (0: No use for thermoelectic power, 1: Use for thermoelectric power)
Percent of a single unit detached	1												
percent of structure built since year 1990	-.009	1											
Average household size	-.047	.339**	1										
LN median HH income	.014	.234**	.191**	1									
LN population density, person/sqmile	-.364**	-.012	.054*	.418**	1								
Percent of lev 3 employment: manufacturing	.283**	-.068**	-.058*	-.235**	-.154**	1							
Pecent of lev 4 employment: wholesales, retail sales, warehousing	.071**	.092**	.178**	-.046	-.118**	-.309**	1						
Percent of lev 5 employment: information, FIRE, tech services	-.369**	.065**	.040	.510**	.649**	-.458**	-.089**	1					
Percent of lev 6 employment: education and health service	-.099**	-.350**	-.129**	-.252**	.037	-.318**	-.029	-.043	1				
LN Long-term averages of annual average temperature, 1980-2010 normals	-.199**	.296**	.276**	-.256**	.170**	-.050*	.093**	.054*	-.086**	1			
LN Long-term averages of annual precipitation totals	.010	.008	-.229**	-.126**	.289**	.190**	-.047	-.031	.022	.311**	1		
Dummy: Metro (0: Not metro 1: metro)	-.186**	.222**	.196**	.490**	.574**	-.258**	.004	.476**	-.035	.117**	.002	1	
Dummy: Thermoelectric Power (0: No use for thermoelectic power, 1: Use for thermoelectric power)	-.146**	-.123**	-.013	.141**	.280**	-.138**	-.017	.248**	.059*	.031	-.020	.217**	1

Table 8: The Final List of Dependent and Independent Variables in Regression Models

Type	Categories	Variables	Unit	Data Frequency	Data Sources
Dependent Variable	Water use	Per capita water use rate by county: (1) total water use, (2) urban water use (3) domestic	Gallon per day	Year 2005	Water Use Data, (US Geological Survey / EPA)
Independent variables	Urban form / Built environment characteristics	Percent of single family units detached	Percent (%)	Annual	US Census/American community survey 2005-2007, 3-year estimates
		Percent of structure built since year 1990	Percent (%)	Annual	US Census/American community survey 2005-2007, 3-year estimates
		Population density	Person/ acre	Annual	US Census year 2005-2007, 3-year estimates, US Census GIS Data (County)
	Demographic/ Economic characteristics	Average household size	Person	Annual	US Census/American community survey 2005-2007, 3-year estimates
		Median household income	Dollars	Annual	US Census/American community survey 2005-2007, 3-year estimates
		Percent of manufacturing employment	Percent (%)	Annual	US Census County Business pattern 2005
		Percent of wholesale and retail employment	Percent (%)	Annual	US Census County Business pattern 2005
		Percent of information, FIRE, and technology service employment	Percent (%)	Annual	US Census County Business pattern 2005
		Percent of education and health service employment	Percent (%)	Annual	US Census County Business pattern 2005
	Climate variability	Average annual temperature, 30-year Normals	˚F (Fahrenheit)	Annual	National Oceanic and Atmospheric Administration (NOAA), National climate data center, 30 year 1980-2010 Normals
		Average annual precipitation, 30 year Normals	Inch	Annual	National Oceanic and Atmospheric Administration (NOAA), National climate data center 30 year 1980-2010 Normals
	Dummy variables	Inside metropolitan area	0: Not Metro 1: Inside Metro		US Census/American community survey 2005-2007, 3-year estimates
		Thermoelectric Power	0: No substantial withdrawal for thermoelectric power 1: Substantial water withdrawal for thermoelectric power		Water Use Data, (US Geological Survey / EPA)

RESULTS

SUMMARY STATISTICS OF VARIALBES AND MODELS

The county-level analysis tests the correlation between the set of independent variables defined earlier and three different types of per capita water use. The per capita water use rate is represented as a gallon per capita per day (thereafter, GPCD). The Table 7 presents the summary statistics of three different types of variables (total water use rate, urban water use rate, and domestic water use rate) with a series of independent variables. When the variables are transformed into logarithm, the original values in the variables were reported in this summary statistics.

In terms of the means of water use rates, total water use, urban water use, and domestic use in selected counties were 1,664 gallons, 730 gallons, and 95 gallons, respectively. Figure 18 shows the geographic representations of GPCDs at county scale in urban water use. High values in total water use and urban water use in certain counties were expected because most counties with extremely high GPCDs tend to withdraw a large amount of water for agricultural use and thermoelectric power use; however, they also tend to have relatively a small number of population in their counties; hence the relatively high per-capita value.

In terms of the variance of water use rates, the three different dependent variables of observed counties all vary substantially, although the domestic use rate shows less variance than the other two.

Table 9: Summary Statistics of Variables of Interest: County Level Analysis

	N	Minimum	Maximum	Mean	Std. Deviation
GPCD, Total water withdrawl	1,590	2	97,684	1,644	4,558
GPCD, Urban Water	1,590	1	18,973	730	1,878
GPCD, Domestic total	1,590	6	615	95	45
Total Population in county	1,590	19,032	9,935,475	169,952	415,738
Total Employment in county	1,590	0	3,895,886	69,214	186,241
Percent of a single unit detached	1,590	0.3	88.8	68.6	9.9
percent of structure built since year 1990	1,590	4.1	76.5	26.4	11.1
Median household income (2007)	1,590	20,586	104,612	45,038	11,509
Average household size	1,590	2	4	3	0
Employ Lev 3: manufacturing	1,590	0	473,532	7,785	18,672
Employ Lev 4: wholesale trade, retail trade, transport and warehousing	1,590	94	860,090	15,253	39,346
Employ Lev 5: information, FIRE, professional scientific, tech services	1,590	54	1,244,715	18,510	64,518
Employ Lev 6: education, heallth service	1,590	0	556,589	11,356	29,099
Percent of lev 3 employment: manufacturing	1,590	0.0	61.4	17.2	11.2
Pecent of lev 4 employment: wholesales, retail sales, warehousing	1,590	0.0	55.0	23.2	4.9
Percent of lev 5 employment: information, FIRE, tech services	1,590	0.0	55.7	16.0	7.5
Percent of lev 6 employment: education and health service	1,590	0.0	63.8	16.6	5.9
Population density (persons/mile2)	1,590	2	58,417	395	2,163
Employment density (persons/mile2)	1,590	0	74,623	194	1,951
Long-term averages of annual average temperature, 1980-2010 normals (Farenheit)	1,590	28.1	76.2	55.0	7.9
Long-term averages of annual precipitation totals (inches)	1,590	3.2	89.2	41.2	12.8
Long-term averages of annual cooling degree days with base 65F, 1980-2010 normals	1,590	1	4,275	1,236	822
Long-term averages of annual heating degree days with base 65F, 1980-2010 normals	1,590	3	13,509	4,876	2,125
Dummy: Metro (0: Not metro 1: Metro)	1,590	0.0	1.0	0.5	0.5
Dummy: Thermoelectric Power (0: No use for thermoelectic power, 1: Use for thermoelectric power)	1,590	0.0	1.0	0.3	0.5

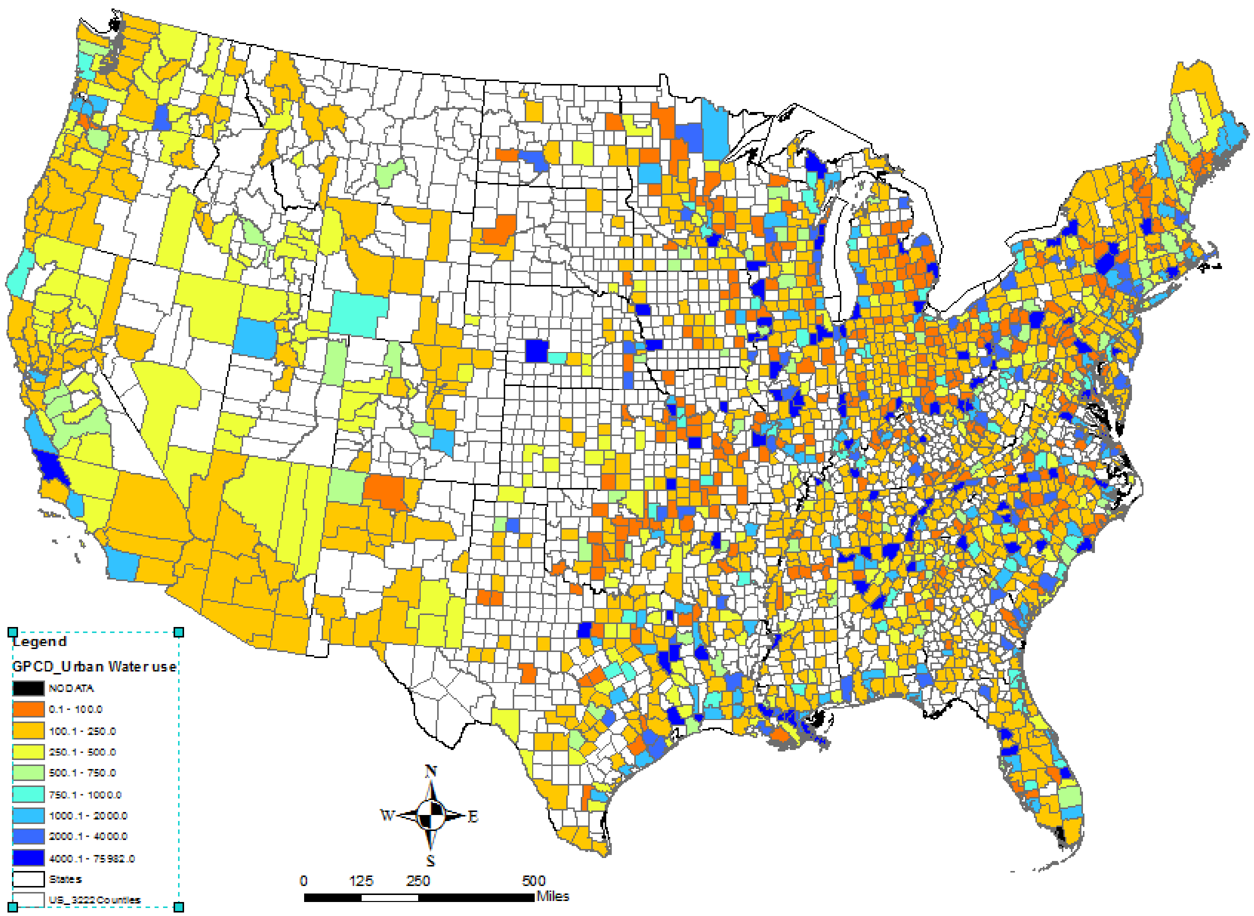


Figure 18. Urban Water Use in Gallon per capita per day (GPCD)

MODEL SUMMARY

Table 10 – Table 15 show the results of the three models' summaries in terms of R-squared, errors in residuals, and coefficients. In the tables, Model 1 refers to the regression model with a logarithm of total water use GPCD as a dependent variable. Model 2 refers to the regression model with a logarithm of urban water use GPCD as a dependent variable. Model 3 refers to the regression model with a logarithm of domestic water use GPCD as a dependent variable.

In terms of goodness of fit for the regression models, adjusted R-squared values from Model 1, Model 2, and Model 3 were .347, .340, and 0.274, respectively. F statistics (DF = 13) for the Model 1, 2 and 3 were 65.96, 63.97, and 67.52, respectively, and they are all significant (p=0.00). In three models, the Durbin-Watson statistic, which tests for the presence of serial correlation among the residuals, was 1.97 (Model 1), 1.935 (Model 2), and 2.052 (Model 3). In general, the residuals are uncorrelated when the Durbin-Watson statistic is approximately 2, suggesting that no serial correlation among residuals existed in three models.

Table 10: Model Summary: Total Water Regression Model

Model	R Square	**Adjusted R Square**	Std. Error of the Estimate	Durbin-Watson	ANOVA F	ANOVA Sig.
1	.352	**.347**	1.150535	1.970	65.96	.000

Dependent Variable: LN GPCD Total Water use
Regression df = 13, regression mean square = 85.316, residual mean square=1.324

Table 11: Model Summary: Urban Water Regression Model II

Model 2	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson	ANOVA F	ANOVA Sig.
	.345	**.340**	1.0123891	1.935	63.97	.000

Dependent Variable: LN GPCD Urban water use
Regression df = 13, regression mean square = 65.571, residual mean square=1.025

Table 12: Model Summary: Domestic Water Regression Model III

Model3	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson	ANOVA F	ANOVA Sig.
	.278	**.274**	.3361230	2.052	67.52	.000

Dependent Variable: LN GPCD Domestic water use
Regression df = 9, regression mean square = 7.628, residual mean square=0.113

Coefficients estimates significance and signs of influence

Several independent variables of interest in three models showed consistent results in terms of signs of coefficients and statistical significance. First, two urban development configuration variables, percent of structure built since year 1990 and population density (log), were significantly negatively (-) correlated with daily per capita water use (GPCD). The variable of percent of single family unit detached was significant in Model2 (urban water use GPCD) and Model 3 (domestic water use GPCD); however, its sign of coefficients were mixed.

Second, regarding socio-economic variables, median household (HH) income (log) was significant variable in three models that are positively (+) correlated with GPCD; however, the average household size variable was positively (+) correlated with domestic GPCD (Model3), but not with the others.

Third, regarding the variables associated with county sectoral employment configurations, the variables of the percent of SIC level 4 employment-wholesale trade, retail trade, and warehousing (positive impact: +) and the percent of SIC level6 employment-education and health service (negative impact: -) were significant in Model 1; however, in the other models, they were not significant. When other conditions are equal, the county with higher percentage of employment in the wholesales, retails and warehousing business turns out per daily per capita water use were high, which is expected.

Forth, in climate related variables, averages of annual average temperature were consistent and significant variable (positive impact: +) positively correlated to all GPCD types. Long-term averages of annual precipitation totals were significant. However, the sign of coefficient for Model 1 and 3 were negative (-) whereas it was positive (+) in Model 2, suggesting further studies are needed.

Lastly, the variable of massive withdrawal for thermoelectric power (Dummy) was significant in Model 1, and Model2, but not in Model 3. The variable representing whether the county is inside of Metro was only significant for Model 2.

Table 13: Results: Summary of Coefficients Estimates: Total Water Regression Model I

Dependent: LN GPCD Total Water		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Std. Coefficients Beta	t	Sig.
Urban development configuration	(Constant)	.443	2.621		.169	.87
	Percent of a single family unit detached	-.004	.003	-.026	-1.065	.29
	Percent of structure built since yr. 1990	**-.013**	.003	-.098	-3.892	.00***
	LN population density (person/mile2)	**-.418**	.04	-.382	-10.54	.00***
Socioeconomic (Household)	Average household size	.152	.151	.025	1.006	.31
	LN median HH income	**.383**	.194	.064	1.968	.05**
Employment	Percent of lev 3 employment: manufacturing	-.002	.004	-.017	-.544	.59
	Percent of Lev 4: wholesale trade, retail trade, transport and warehousing	**.014**	.007	.049	2.078	.04**
	Percent of Lev 5: information, FIRE, professional scientific, tech services	-.002	.006	-.01	-.295	.77
	Percent of lev 6 employment: education and health service	**-.014**	.006	-.06	-2.267	.02**
Climate - Related (NCD 1980-2010, 30- year normals)	**Long-term averages of annual average temperature, 1980-2010 normal**	**1.596**	.276	.161	5.787	.00***
	Long-term averages of annual precipitation totals	**-.83**	.089	-.241	-9.349	.00***
Dummy	Dummy: Metro (0: Not metro 1: metro)	.034	.079	.012	.43	.67
	Dummy: Thermoelectric Power (0: No use 1: Use)	**1.334**	.067	.433	20.01	.00***

***: p=0.01, **: p = 0.05, *: p = 0.10

Table 14: Results: Summary of Coefficients Estimates: Urban Water Regression Model II

Dependent: LN GPCD Urban Water		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Std. Coefficients Beta	t	Sig.
Urban development configuration	(Constant)	-1.744	2.306		-.756	.450
	Percent of a single unit detached	**.005**	.003	.039	1.606	.100*
	Percent of structure built since yr. 1990	**-.008**	.003	-.070	-2.758	.006***
	LN population density (person/mile2)	**-.186**	.035	-.195	-5.348	.000***
Socioeconomic (Household)	Average household size	-.027	.133	-.005	-.205	.838
	LN median HH income	**.352**	.171	.067	2.058	.040**
Employment	Percent of lev 3 employment: manufacturing	.004	.003	.035	1.126	.261
	Percent of Lev 4: wholesale trade, retail trade, transport and warehousing	-.003	.006	-.013	-.536	.592
	Percent of Lev 5: information, FIRE, professional scientific, tech services	-.003	.006	-.017	-.502	.616
	Percent of lev 6 employment: education and health service	-.005	.006	-.025	-.953	.341
Climate -Related (NCD 1980-2010, 30- year normals)	**Long-term averages of annual average temperature, 1980-2010 normals**	**.851**	.243	.098	3.506	.000***
	Long-term averages of annual precipitation totals	**.126**	.078	.042	1.610	.100*
Dummy	**Dummy: Metro (0: Not metro 1: metro)**	**.208**	.069	.083	2.992	.003***
	Dummy: Thermoelectric Power (0: No use for thermoelectric power, 1: Use for thermoelectric power)	**1.598**	.059	.592	27.236	.000***

***: p=0.01, **: p = 0.05, *: p = 0.10

Table 15: Results: Summary of Coefficients Estimates: Domestic Water Regression Model III

Dependent: LN GPCD Domestic Water		Unstandardized Coefficients		Std. Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	-1.129	.683		-1.652	.099**
Urban development configuration	**Percent of a single unit detached**	**-.005**	.001	-.119	-4.911	.000***
	Percent of structure built since yr. 1990	**-.003**	.001	-.086	-3.341	.001***
	LN population density (person/mile2)	**-.083**	.010	-.274	-8.213	.000***
Socioeconomic (Household)	**Average household size**	**.144**	.042	.085	3.389	.001***
	LN median HH income	**.247**	.050	.149	4.910	.000***
Climate - Related (NCD 1980-2010, 30- year normals)	**Long-term averages of annual average temperature, 1980-2010 normal**	**1.129**	.078	.412	14.512	.000***
	Long-term averages of annual precipitation totals	**-.309**	.025	-.326	-12.482	.000***
Dummy	Dummy: Metro (0: Not metro 1: metro)	.000	.023	.000	.015	.988
	Dummy: Thermoelectric Power (0: No use for thermoelectric power, 1: Use for thermoelectric power)	-.001	.019	-.002	-.067	.946

***: p=0.01, **: p = 0.05, *: p = 0.10

MAJOR FINDING AND DISCUSSIONS

INTERPRETATION OF COEFFICIENTS OF POLICY CONTROLLABLE VARIABLES

Population density (policy variable)

The analyses results suggest that some policy variables are significantly correlated with changes in water use levels. Especially, the population density variable shows the consistent results. There is a negative correlation between population density and GPCDs in three different types of models, which suggest that higher county population density is related to lower daily per-capita water use. Because the dependent variables in Model 1 (Total water), Model 2 (Urban water), and Model 3 (Domestic) and the population density variable are log transformed, the ratio of the any increase or decrease for population density becomes the ratio of two outcome variables , holding all other variables constant.

For example, the coefficient *(b)* of logarithm of population density (person/mile2) in Model 1 (total water) is -.418 (*b*). Therefore for any 10% increase in county population density, the expected ratio of the two geometric means for county population density will be (1.10)^ *b = 1.10^(.418) = 0.96094*. In other words, we expect about 4 percent (= 1 - 0.96094) decrease in county total water GPCD when county population density increase by 10 percent. For the Model 2 and Model 3 cases, we can calculate each ratio of the expected means of each geometric mean for the county urban water GPCD and county domestic GPCD as (1.10)^ (-.186) = 0.9824 and (1.10)^ (-.083) = 0.9921, respectively. In other words, we can expect about 1.76 percent decrease in county urban water GPCD and 0.79 percent of decrease in county domestic water GPCD when the county population density increases by 10 percent, all other variables held constant.

Similarly, changing levels of population density in the three models can capture the expected ratio of the outcome dependent variable, the county GPCD. Table 16 ~19 summarize the expected ratio of the outcome and GPCD change in percent across different density increases.

Table 16. Expected Ratio of the GPCD Changes: 5 % Increase Population Density

Water Use Types	Coefficient (b)	Density Increase in percent (α)	Ratio of the expected means of dependent variable ($[1+\alpha)^b]$)	GPCD Change in percent $[(1+\alpha)^b]$ -1
Total Water Use	-0.418	5%	0.979812268	-2.02%
Urban Water use	-0.186	5%	0.990966083	-0.90%
Domestic Water Use	-0.083	5%	0.995958605	-0.40%

Table 17. Expected Ratio of the GPCD Changes: 10 % Increase Population Density

Water Use Types	Coefficient (b)	Density Increase in percent (α)	Ratio of the expected means of dependent variable ($[1+\alpha)^b]$)	GPCD Change in percent $[(1+\alpha)^b]$ -1
Total Water Use	-0.418	10%	0.960943509	- 3.91%
Urban Water use	-0.186	10%	0.982428518	-1.76%
Domestic Water Use	-0.083	10%	0.992120463	-0.79%

Table 18. Expected Ratio of the GPCD Changes: 15 % Increase Population Density

Water Use Types	Coefficient (b)	Density Increase in percent (α)	Ratio of the expected means of dependent variable ($[1+\alpha)^b]$)	GPCD Change in percent $[(1+\alpha)^b]$ -1
Total Water Use	-0.418	15%	0.943253234	-5.67%
Urban Water use	-0.186	15%	0.974339259	-2.57%
Domestic Water Use	-0.083	15%	0.988466782	-1.15%

Table 19. Expected Ratio of the GPCD Changes: 30 % Increase Population Density

Water Use Types	Coefficient (b)	Density Increase in percent (α)	Ratio of the expected means of dependent variable ($[1+\alpha)^b]$)	GPCD Change in percent $[(1+\alpha)^b]$ -1
Total Water Use	-0.418	30%	0.896131366	-10.39%
Urban Water use	-0.186	30%	0.95237182	-4.76%
Domestic Water Use	-0.083	30%	0.978459156	-2.15%

According to the analysis results and the Tables, if a county's population density increased by 5 percent, the county GPCD for the total water, urban water, and domestic water would decrease by 2.02 percent, 0.90 percent, and 0.40 percent, respectively when the other predictor variables at any fixed value (Table 16). In other words, if the county's planning body set the goal of reducing county total water use GPCD reduction by close to 2 percent, active promotion of compact-growth policies could help increase county population density by 5 percent. However, to raise the overall population density, the new population density should be raised by a larger factor, since in the great majority of already developed areas density is not likely to change by much.

In general, sprawl or low-density residential development in suburban areas, have been considered as to be non-sustainable urban growth patterns in literature. This analysis suggests that high-density urban development configuration or compact growth policy would be able to reduce per capita daily water use in the county.

Percent of a single family housing unit detached variable (policy variable)

The variable of PSFH was statistically significant in Model 2 and Model 3; however, their signs were mixed, which suggests that further studies are needed in future. In general, a low percentage of single family housing unit or a high percentage of multi-family housing in a county is attributed to more compact urban development settings. As discussed with the population density variable, more compact development pattern is negatively correlated with the per capita water use. Between two models, the Model 2 (urban water use GPCD) is more interesting because of the positive signs of the coefficient of the PSFH variable.

Because the PSFH variable is not log-transformed, the exponentiated coefficient Exp(*b)* for the PSFH variable becomes the ratio of the expected geometric means of the original outcome variable. For example, for a ten-unit decrease (-10 percent) in the PSFH, we expect to see about - 4.88 percent change in the urban GPCD since Exp[0.0050 * (-10)] = 0.951229425 when other variables are held at fixed values. Table 20 shows the urban water use GPCD changes in percent with 5 percent and 20 percent decrease in the PSFH variable.

Table 20. Ratio of the GPCD Change: PSFH Variable

Water Use Types	Coefficient (*b*)	Percentage change in the SFH unit detached variable (θ)	Ratio of the expected means of dependent variable [Exp (*b* *θ)]	GPCD Change in percent [Exp(*b* *θ)]-1
Urban Water use	0.005	-5	0.975309912	-2.47%
		-10	0.951229425	-4.88%
		-20	0.904837418	-9.52%

In this analysis, the mean of county percent of SFH is 68.6 percent. Hence, in order to reduce the urban water use GPCD by about 2.5 percent, the goal of percentage of SFH should be approximately close to 63.6 percent (=68.6 - 5). Similar to population density, in order to drop the overall county percentage of SFH, the new percentage of SFH for new development should be raised by a larger factor because the percent of SFH in most already developed areas will not change by much.

<u>Excessive water use for thermoelectric power variable (Dummy, policy variable)</u>

The thermoelectric power variable (THP, hereafter) is a significant predictor with positive sign in coefficient in Model 1 and Model 2. Because in both models, the dependent variable is log-transformed and the THP is a non-logged dummy variable, its exponentiated coefficient is the ratio of the geometric mean for one group to the other group. Therefore, for total water use, the expected percentage increase in geometric mean from the county group with excessive water withdrawal for thermoelectric power generation to the county group without such use is about 379 percent holding other variables constant, since Exp (1.334) = 3.796197. Similarly, for urban water use, the expected percentage increase in mean from the county group with excessive water withdrawal for thermoelectric power generation to the county group without such use is about 494 percent (EXP(1.598) = 4.94313, holding other variables constant.

Table 21. Ratio of the GPCD Change: Thermoelectric Power Plant (THP) Variable

Water Use Types	Coefficient (*b*)	Ratio of the expected geometric means of the original outcome variable [Exp(*b*)]	GPCD Change in percent
Total Water Use	1.334	3.79619785	379.62%
Urban Water use	1.598	4.943136259	494.31%

Typically, a power plant withdraws substantial amount of water for cooling from a river, but returns waters directly to a river for use by the next downstream users. Hence, it is less demanding than other uses, such as irrigation. However, substantial withdrawal of water from streams may impact community or county during short-term drought.

INTERPRETATION OF COEFFICIENTS OF BACKGROUND VARIABLES

Percent of structure built since year 1990 (background variable)

The percent of structure built since year 1990 (PSTR, hereafter) is the predictor to show the relationship between the overall age of building stocks in county and the county per capita water use rates. According to all three regression models, higher percentage of newer structures in counties corresponds to a lower per capita water use in counties. In other words, the more recently built structure in the county, the lower the daily per capita total water use. The negative sign of coefficient for PSTR variable is as this study expected because newer houses likely to have more efficient water devices than old houses. In particular, as one-unit increase in PSTR, we expect to see about 1.29 percent decrease in total water use GPCD since EXP(-0.013 * 1) = 0.98708413. For urban water use, a 1 percent increase of PSTR, would lead to a 0.8 percent decrease in urban water use GPCD.

Table 22. Ratio of the GPCD Change: PSTR Variable

Water Use Types	Coefficient (*b*)	Change in percent of structure built since 1990 (θ)	Ratio of the expe cted means of de pendent variable [Exp (*b* *θ)]	GPCD Change in percent [Exp(*b* *θ)]-1
Total Water Use	-0.013	1	0.987084135	-1.29%
Urban Water use	-0.008	1	0.992031915	-0.80%
Domestic Water Use	-0.003	1	0.997004496	-0.30%

This is in line with many recent studies that per-capita water use in the United States for the last few decades has gradually declined (Gleick 2003) , presumably owing to technological improvements in water device efficiency. The PSTR variable is categorized as a background variable because age of buildings or overall percentage of buildings stock after 1990 is not controllable by policy. However, a consistent negative sign of coefficients of the PSTR variable indicates that we can expect a gradual reduction in per capita rates as new housing structures with improved water efficiency measure (technological solutions) are added in overall housing stocks.

Median Household Income (background variable)

Median household income (INC, hereafter) is to see the relationship between affluence level as a background variable and the county water use rates. The analysis results suggest that for any 10 percent increase in INC, the expected ratio for the two geometric means in total water use will be (1+.10)^ *b*= 1.10 ^0.383 = 1.0371, which is 3.72 percent increase. For urban water use and domestic water use, we expect about 3.41 percent and 2.38 percent increase in each GPCD when incomes increase by 10 percent (Table 23).

Table 23. Ratio of the GPCD Change: INC Variable

Water Use Types	Coefficient (*b*)	Percent change in income (α)	Ratio of the e xpected mea ns of depend ent variable ([1+α)^*b*])	GPCD Change in percent [(1+ α)^*b*] -1
Total Water Use	0.383	10%	1.037178244	3.72%
Urban Water use	0.352	10%	1.034118304	3.41%
Domestic Water Use	0.247	10%	1.023820906	2.38%

Climate variables: temperature and precipitation (background variables)

The temperature (TEMP, hereafter) variable in three models showed consistent coefficient signs. The warmer the climate, the greater the county GPCD for total water use, urban water use, and domestic water use. However, the relationship between GPCD and precipitation was more ambiguous, with different models producing differently signed coefficients.

Inside Metro or Not-inside Metro variable (Dummy, background variable)

The variable of Inside Metropolitan statistical area or MSA (INMSA, hereafter) is found to be a statistically significant predictor with positive sign for the coefficient only in Model 2 (urban water use). Because the INMSA is a non-logged dummy variable, its exponentiated coefficient is the ratio of the geometric mean for one group (counties inside MSA) to the other group (counties not inside MSA). We see a 123 percent (EXP(.208) = 1.2312131) increase in the geometric mean for the urban water use county GPCD from the county group outside the MSA to the county group inside the MSA, holding other variables constant (Table 24) .

Table 24 Ratio of the GPCD Change: INMSA Variable

Water Use Types	Coefficient (*b*)	Ratio of the expected means of dependent variable [Exp(*b*)]	GPCD Change in percent
Urban Water use	0.208	1.23121317	123.12%

POLICY IMPLICATION FOR SUSTAINABLE WATER USE

This study concludes that policy-control variables associated with urban form and urban development are significantly correlated with water use although the magnitude of influence on water use by such variables require more discussions. Although the exact strength of the relationship should be estimated with caution, it is reasonable to state that increasing the density of single-family residential land development would lead to a long-term reduction in per capita water use although the magnitude of changes would be very modest.

Then, how much can we reasonably set the goal for population density to change? Let's assume a hypothetical scenario. To increase overall density by 10 percent, the density for new development areas would need to increase by a much higher percentage, since it would be more difficult to increase density in already-developed areas. Therefore, a county pursuing an overall population density increase should set the target of population density for new development much higher than the average density at present by 10 percent. In a hypothetical scenario that a county with 100,000 people and all population resides in an urbanized area of 100 square miles for an urban/suburban density[2] of 1,000 persons per square mile. Over the number of years, the county adds another 20,000 people. In this case, the density of new development areas should be approximately 2,222 persons per square mile (=20,000 persons / 9 square miles) to produce a 10 percent density increase (1,100 persons = 120,000 persons / 109 square miles). Hence, even doubling the future development density would reduce total ware use rate only by 4 percent, urban water use by 1.75 percent and domestic water use by 0.79 percent.

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[2] In this hypothetical scenario, urban density and county population density are considered similar concepts. Actual urban density would be different from county population density depending on urbanized patterns.

Then, compared to strategies that emphasize technological advances (such as the increased efficiency of water devices), how effective is this land use development configuration approach in moderating future water use growth? Vickers (2001) states that water efficient fixtures for indoor use can reduce the daily capita water use by 24 gallons (=69.3-45.3). The EPA report , 'Water Sense Single-Family New Home Specification' (2009), also suggests that a daily per capita water use for a single-family home can be reduced by 10.3 gallons (= 49.8 -39.5) (EPA 2009). Comparing to these technological solutions, two gallons per capita per day reduction through population density increase less. Furthermore, the water saving outcome of technological solutions are expected to occur much more quickly than would reductions resulting from changes in land use, which are harder and more time-consuming to implement.

Even so, estimating future population and that population's projected water consumption is critical when estimating water demand. According to Metropolitan North Georgia Water Planning District (MNGWPD, 2009, page 3-6), weighted average of overall GPCD for 15 counties (13 counties in Chapter 6 + Bartow and Hall) is 127 gallons. If a successful growth control policy increased population density in a given county by 10 percent over the next 30 years, said county would expect approximately a decrease of 2.23 GPCD (-1.76 percent * 127=2.23), according to Table 17 above. Atlanta Regional Commission (ARC, hereafter), the regional planning agency, predicts an increase in metropolitan-area population from 4.55 million in 2010 to 6.84 million in 2040 (see Table 1 previously). Density increases would result in a total volume of water savings of 15.1 million GPCD (6.8 million * 2.23 GPCD = 15.1 million gallons per day for 13 counties). Therefore, to say that land-use changes would result in smaller water-use savings than the use of more efficient devices is not to imply that such changes would be ineffective.

CHAPTER SUMMARY

This chapter discussed the relationship between county daily water use rates and a series of independent variables, including those related to urban development configuration. On the basis of empirical data across 1,590 counties in the United States, This study suggests that an increase in county population density and increase in percentage of multi-family housing (or decrease of percentage housing that is single-family) would promote more sustainable water use through per capita water use reduction , although the magnitude of such reduction would be very modest.

The empirical findings suggest that urban form and growth policy would play a role in GPCD reduction, although such change would not achieve greater water savings than other proposed policy options, such as technological solutions. The next step of this research is to refine the unit of analysis at a level more precise than that of the county. The next chapter will discuss water consumption at the parcel level to determine the possible relationship between annual water use and residential lot size, which is also related to urban form and development configuration.

CHAPTER 4

PARCEL LEVEL DATA ANALYSIS

In the previous chapter, the county level analysis tested the relationship between the predictor variables related to urban form-land use and other background variables and the dependent variables of per-capita urban water use rates. The parcel level analysis in this chapter has a more narrow focus, intended to find a range of residential annual water use factors at the household level.

In general, a large size lot with high property value has a large size of lawn (Syme, Shao et al. 2004) and often includes an outdoor pool (Domene and Saurí 2006, Wentz and Gober 2007) which would consume more seasonal outdoor water. The argument in this research design is that smaller lot sizes tend to reduce the volume of annual water use when other conditions are held constant; hence compact residential development is more desirable to support sustainable urban water use. In the parcel-level analysis, a residential lot size variable and a property value (as a proxy of income) variable explain annual water use at household level.

RESEARCH METHOD AND DESIGN

ANALYSIS OBJECTIVES AND A MODEL SPECIFICATION

In this chapter, this study investigates whether a larger lot size would derive a higher volume of water consumption in residential use. The measure of water volume in the parcel level analysis is actual water billing data recorded from 2006 to 2008 by individual households or entities in several cities in Fulton County, Georgia.

DATA COLLECTION AND DATA PRE-PROCESSING EFFORTS

One of major challenges in carrying out the study of the parcel level analysis were to collect and process the billing records of water use at household level, which required manual processing of data such as aggregating water use statistics with inconsistent billing periods by addresses or by geographic jurisdictions. Data collection and pre-process began with compiling available data obtained from Fulton County Water and Billing Service and Fulton County, Georgia. The county provided the water billing records of individual accounts or premises of cities in Fulton County, Roswell, Johns Creek, and Alpharetta between 2006 and 2008. The dataset was delivered as a plain text file containing the information of volume of water billed (in gallons) with a variety of billing periods or terms such as monthly, bi-monthly or tri-monthly. It also contained addresses of accounts or premises, account IDs, and device ID(s) in case multiple water devices were associated with a single account.

Although the original dataset contained total of 50,874 account observations over three years, several steps of selection process were necessary in order to obtain analyzable data. First, the plain text file was imported into Excel spreadsheet format dataset. Then the accounts with any zero value in billing records, which represents a temporary account closure, were removed to calculate accurate annual water volume by premise. Second, this study only used the water billing records between January 2006 and December 2006 to calculate annual water use because Georgia experienced one of the worst water droughts in history during the summer of 2007 and 2008, which resulted in a state of emergency for 85 counties in the northern part of the state[3]. The resulting restriction of outdoor watering would skew reported water uses. Third, a sample observation set was compiled only when the account or premise has been billed with a consistent billing period terms of bi-monthly, either a billing set starting from January (Month 1, 3, 5, 7, 9, 11) and ending in November or a billing set starting from February and ending in December (Month 2, 4, 6, 8, 10, 12). Because cities in north Fulton County have inconsistent billing periods in the report file, several billing periods were classified into multiple groups and the records were filtered to remove duplicates and avoid gaps. Although this selection process reduced a sample size of observations, this was inevitable to maintain the accuracy level of total annual volume of water use calculation for individual account.

Lastly, in order to combine the water billing records and Fulton county GIS parcel database in year 2006, address matching process through attribute join was carried out in ArcGIS GIS Software (ESRI Inc.). The GIS parcel database (year 2006) provided by Fulton County Tax Assessor contained the attribute fields of address, area of lot in acre, land use or zoning types, total assessed value, land value, improved value of buildings, building construction date, number of stories of buildings. When performing attribute joins, a two-step selection process was applied. First, only single family residential parcels in the GIS database are selected and joined with water billing records. Second, the parcel with the lot size less than 4 acres were only selected in order to remove outliers in

[3] Stacy Shelton and Rhonda Cook, "2008 Summer Drought Survival Guide: Where We Are with the Water," Atlanta Journal-Constitution, May 25, 2008, sec. A.

the regression analysis. The address field on both GIS parcel database and the water billing record set was used as the key field in joining operation. Finally, 15,594 records of selected parcel features in three cities were exported as a shape file format. Figure 19 and Table 25 show the geo-referenced locations of customer billing records from the final regression analysis dataset.

Table 25. Number of Observations after Address Matching in the Parcel Level Analysis

Billing months and the city	Roswell	Johns Creek	Alpharetta	Total
Billing months in February, April, June, August, October, and December	3,999	4,255	256	8,510
Billing months in January, March, May, July, September, and November	*	6,902	182	7,084
Total number of observations	3,999	9,157	438	15,594

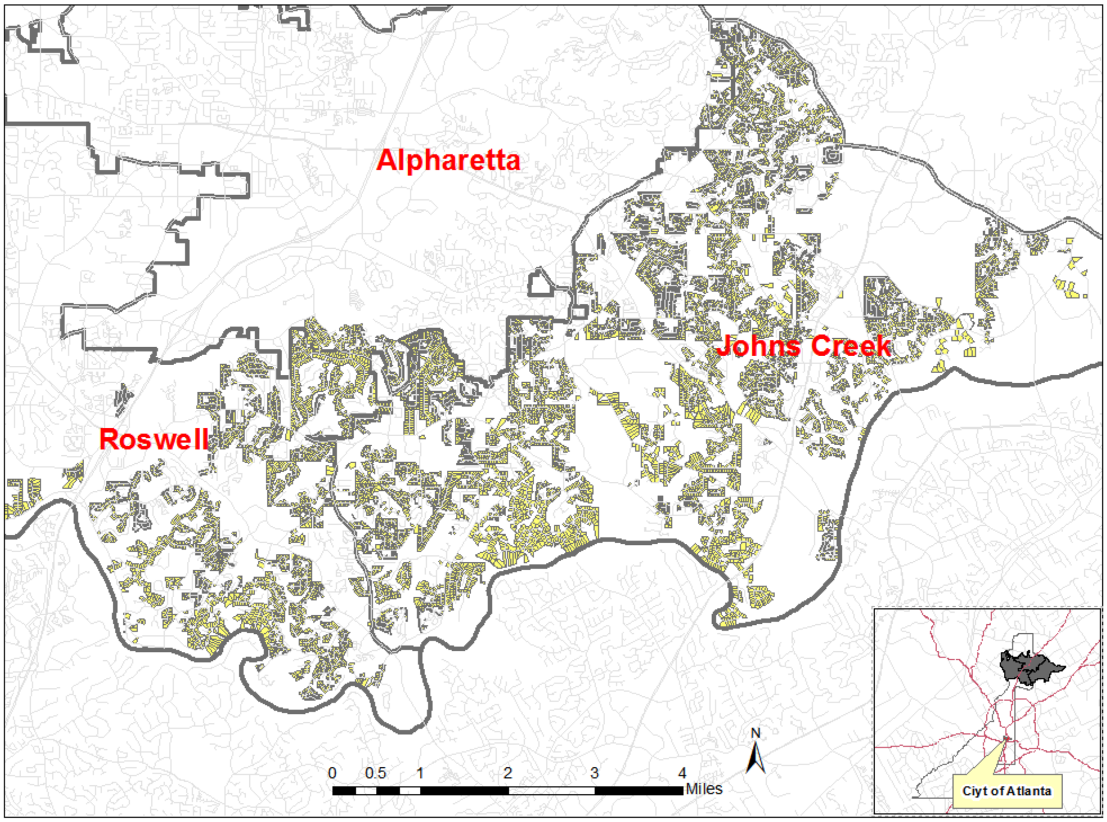


Figure 19. Study Area of Parcel Level Analysis: Address-matched Locations with Water Use Billing Records

DATA EVALUATION AND REGRESSION ANALYSIS DESIGN

In terms of a research method, the parcel-level analysis is similar to the county-level analysis because results and discussions are also derived from a regression analysis method. However, two things are different in terms of the model specifications; (1) for the parcel level analysis, the dependent variable is an annual volume of water used in a single year at household level, and; (2) in addition to OLS model specification, spatial error model specification is tested in order to resolve spatial autocorrelation issues.

Dependent and independent variables of interests

In this parcel-level analysis, variables of interest are different from the county level analysis. The dependent variable in the parcel-level analysis is not a county representative per-capita water-use rate, but a total amount of water billed to an individual residential account for a year. A list of independent variables of interest in the parcel level analysis is determined while data collection and pre-processing process is carried out. Because of limited socio-economic data availability at individual household level, an extensive list of independent variables, such as number of people in household, household income, existence of outdoor pools, price of water, volume of water leaks, and size of lawns, were not available. In fact, this study favored in a small number of variables in the analysis due to two reasons: a large degree of freedom and minimization of multi-collinearity problems.

Two methods were used to improve the validity of the variables of interests available from the given databases. First, when the distribution of a variable is skewed, the variable is transformed to take logarithm form and put in regression analysis. Second, the multicollinearity issue is examined by conducting a bivariate correlation analysis. If the results suggest there are high correlations (with correlation values larger than 0.8) among pairs of exploratory variables, such variables were not put in regression analysis. The dependent variable (annual volume of water use) was transformed to logarithm in order to make the distribution of observed samples not skewed. Within independent variables, a total assessed value of parcel is included in the variable list as a proxy of household income because the individual household income data is hardly available. Although the living unit variable was also considered as independent variable, it was omitted from the list because it was highly correlated to other independent variables such as the building story variable and the total assessed value variable.

Like the county level analysis in previous chapter, parcel-level analysis distinguished ‘policy control variables’ from ‘background variables.’ In this analysis, the ‘residential lot size’ (LOT, hereafter) variable is a policy control variable, whereas the ‘assessed value in county tax assessor database (ASSESS, hereafter), the structure age (AGE, hereafter), and the building story or floor (FLOOR, hereafter) variables are background variable. The policy variable is marked with ‘*’ symbol below. Finally, the dependent and independent variables are determined as following.

<u>Dependent variable</u>: Logarithm of total annual volume of water billed to a single family residential premise or account from a single year from January 2006 to December 2006 (unit: gallon) (LOG_ANNW, hereafter)

<u>Independent variables:</u>

(1) A residential lot size (LOT) (unit: acre) – policy variable*

(2) A total assessed value in county tax assessor database in 2006 (ASSES) (unit: dollars)

(3) A structure age from 1950: if a structure was built in 2000, the age=50 (AGE) (unit: year)

(4) A number of building stories or floors (FLOOR) (unit: floor)

SPATIAL REGRESSION MODEL ANALYSIS

In the parcel-level analysis, the regression model is designed to quantify the relationship between annual water use and explanatory factors. At the scale of the community or neighborhood, the observed samples in regression sets are geographically near each other in distance than that of the county level analysis, which would raise an issue of a spatial dependence (Anselin and Bera 1998). Typically, standard linear regression or ordinary least squares (OLS) estimation method requires assumptions about the error terms: (a) the sum of error terms would be zero mean (or close to zero); (b) the error terms are not correlated; (c) the error terms are homoscedastic ; and (d) errors follow normal distribution (Weiss and Weiss 2012). However, when a value observed in certain locations depends on the values observed at neighboring locations, these assumptions are not satisfied (Cressie 2015). Following Tobler's first law of geography, "…near things are more related than distant things" (Tobler 1970), the observed variance of variables among samples would be affected by spatial unit (distance). If the things (objects) are close to each other in location and also tend to be similar in attributes, it suggests the existence of positive autocorrelation (Ding and Fotheringham 1992). This reflects the measurement errors or the violation of the random sampling, the nature of underlying process when generating the sample data (Weiss and Weiss 2012). Then, the regression model should be modified to identify and isolate the effects from spatial dependence in the variables and error terms. Unless samples are randomly collected or they are far-distant from each other, locational similarity should be accounted for in the error term when constructing regression models. Therefore, unlike the county-level analysis, the parcel-level analysis includes not only OLS regression models but also a spatial regression model to see if the spatial regression models would suggest improvement in finding a better fit.

In general, spatial regression analysis can improve model accuracy by acknowledging spatial dependence or a property of spatial autocorrelation (Anselin and Bera 1998). Spatial autocorrelation is the formal property that deals with locational and attribute information of geographic objects at the same time (Goodchild 1986, Anselin and

Rey 1991, Ding and Fotheringham 1992). This study assumes that a spatial-regression modeling effort would resolve spatial autocorrelation issue in regression models when samples are collected from which geographically close and nearby.

There are two types of spatial linear regression models; Spatial Lag Model (SLM, hereafter) and Spatial Error Model (SEM, hereafter) (Anselin and Rey 1991, Anselin and Bera 1998). In the SLM, the dependent variable in place *i* is affected by the independent variables in both place *i* and *j*; hence the model suggest that events in one place predict an likelihood of similar events in neighboring places (Anselin, Bera et al. 1996). In the SEM, the error terms across different sample observations are assumed to be correlated, which makes the estimates in OLS regression inefficient (Anselin, Bera et al. 1996). The SEM suggests that the omission of spatial errors would improve the validity of inference (Anselin and Rey 1991).

The parcel-level analysis follows the method for testing for spatial dependence in the SEM, as illustrated in Equation 3, below.

Equation 3. Spatial regression model in parcel level analysis

$$\boldsymbol{WA}_{\boldsymbol{annual\ water\ use\ in\ a\ premise}\ \ \boldsymbol{j}} = \sum_{\boldsymbol{t=1}}^{\boldsymbol{6}} \boldsymbol{W\ t, j}$$

$$= \alpha_0 + \beta_i X_{ij} + \varepsilon_j\ , \quad \varepsilon j = \lambda W \varepsilon + \xi \quad \text{(SEM, Anselin and Bera, 1988)}$$

Where:

t =count of monthly billing months, either the group of 1, 3, 5, 7, 9, 11th month or the group of 2, 4, 6, 8, 10, 12th month.

βi = coefficient of explanatory variable Xi.

X_i = independent variable *i*,

j = location of billing account premises

ε_j = the vector of error terms, sptialy weihtedusing the weightes matrix W,

λ= spatial error coefficient (If no spatial correlation between the errors, then λ = 0

ξ = vector of uncorrelated error term,   W = spatial weight matrix

The series of steps to determine the extent of spatial autocorrelation and run a spatial regression are: (1) choose a neighborhood criterion; (2) create a spatial weights matrix; (3) run a statistical test to examine spatial autocorrelation; (4) run the OLS regression; and (5) run a spatial regression by applying weights matrix.

In this study, the spatial regression statistics software package GeoDa (Anselin 2005) was used to go through these steps and run a spatial regression. First, the GIS shape file dataset (spatial reference or projection: NAD 83 Georgia West State Plane-feet) was imported as a GeoDa project file. Second, the spatial weights matrix file was created with the threshold distance of 1 mile while applying the neighborhood criterion. Once this spatial weights matrix was created, spatial dependency was statistically tested by examining Moran’s I value. Afterwards a simple OLS regression and spatial regression were run to examine signs or directions of coefficients of the variables of interests.

Limitation of data availability makes the analysis hard to suggest a good level of predictive models due to two reasons. First, most social and economic data or variables of interest available at a geographically aggregated scale, such as census block group or census tract level, do not allow for much variability in statistical analysis design. Second, many non-captured variables that would affect the volume of water use at individual consumers' level are hard to be included in this study design. Although limited data availability has prevented from enhancing the accuracy of the predictive model, interpretation of coefficients in results would offer meaningful policy implications in promoting sustainable water use and sustainable urban development configuration at community scale.

RESULTS

SUMMARY OF DESCRIPTIVE STATISTICS

Table 26 presents a list of selected variables and descriptive summary statistics. Particularly, the mean of annual volume of total water use is 105,733 gallons per year per household. The mean value of assessed property values is 345,201 dollars and the standard deviation (STDV) is 220,231. The mean of lost size is 0.4 acre with a STDV value of 0.3. Finally, the average of structure year in the set is 1989 (base year 1950 + mean 39.6). For this variable, the higher the value, the more recently the structure was built.

Table 26: Summary Statistics of Selected Variables- Parcel level analysis

	Minimum	*Maximum*	*Mean*	*Std. Deviation*
Annual total water use (gallon)	1,500	18,696,600	105,733	182,871
Total assessed value in 2006 (dollars)	100	3,711,100	345,201	220,231
Structure floor (stories)	1.0	3.0	1.7	0.4
Lot size in acre	0.0	4.0	0.4	0.3
Structure year since 1950 (built year is pre-1950 or equal, value = 0)	0	55.0	39.6	7.0
Total observation, N = 15,594				

After producing the descriptive statistics of variables of interest, the study also generated the bi-variate correlation matrix to examine multicollinearity. As shown in Table 27, all covariance coefficients in the matrix were low (<.8), suggesting there are few multicollinearity issue raised among independent variables in regression modeling analysis.

Table 27: Correlation Matrix of Variables Selected for Parcel-Level Analysis

	Log annual total water use (gallon)	lot size in acre	total appraisal value in 2006 (dollars)	structure floor (stories)	structure year since 1950 (years)
Log annual total water use (gallon)	1				
lot size in acre	.297**	1			
total assessed value in 2006 (dollars)	.508**	.462**	1		
structure floor (stories)	.070**	-.070**	.089**	1	
structure age from 1950 (years)	.131**	-.074**	.308**	.264**	1

**. Correlation is significant at the 0.01 level (2-tailed).

RESULTS FOR THE OLS REGRESSION MODEL

The OLS regression model predicts a logarithm of total annual volume of water use in a single family residential household (LOG_ANNW) with several the indicators of a size of lot in acre (LOT), an assessed property value in dollors (ASSES), a structure floor (FLOOR), and an age of structure from 1950 in year (AGE). Figure 20 and Table 28 shows the summary information of the run including R-squared, F-test probability and Log-likelihood, the coefficients, the standard error, and significance of independent variables. Major findings in the OLS estimation including spatial dependence are as below.

First, as shown in Figure 20, high F-statistic (1398.5, prob=0.00) suggests the model specification is statistically significant; however the R-squared value (0.264) and the adjusted R-squared value (0.263) suggest that more information or additional indicators are desirable for improvement. Second, the multicollinearity condition number in the regression diagnostics was 18.4653, which suggest no multicollinearity among independent variables. In general, if this number is greater than 20, the model is considered to suffer from multicollinearity (Anselin 2004). Third, the low probabilities (0.00) of Breusch-Pagen test and Koenker-Bassett test results indicated existence of heteroscedasticity. This is not necessarily a surprise as spatial dependence in the dataset, if any, would affect the error variance substantially (Anselin 2004).

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Dependent Variable  :  LN_ANN_GAL  Number of Observations:15594

R-squared           :    0.264086  F-statistic          :     1398.55
Adjusted R-squared  :    0.263897  Prob(F-statistic)    :           0
Sum squared residual:     4663.56  Log likelihood       :    -12715.1
Sigma-square        :    0.299157  Akaike info criterion :    25440.2
S.E. of regression  :    0.546952  Schwarz criterion    :     25478.5
Sigma-square ML     :    0.299061
S.E of regression ML:    0.546865

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   18.465346

DIAGNOSTICS FOR HETEROSKEDASTICITY
TEST                   DF          VALUE             PROB
Breusch-Pagan test     4         1665.9197          0.00000
Koenker-Bassett test   4          748.5837          0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
TEST                          MI/DF        VALUE          PROB
Moran's I (error)             0.0519       47.1653        0.00000
Lagrange Multiplier (lag)       1        1302.2675        0.00000
Robust LM (lag)                 1         242.6808        0.00000
Lagrange Multiplier (error)     1        2160.7068        0.00000
Robust LM (error)               1        1101.1202        0.00000
Lagrange Multiplier (SARMA)     2        2403.3876        0.00000
```

Figure 20: Summary of Output: Parcel Level Analysis - OLS

Coefficients estimates and their interpretations

Table 28 summarized the coefficients (B or *b*) of indicators and significance of estimates. Among the four independent variables, LOT, ASSESS, and FLOOR positively related to annual water use volume (LOG_ANNW), while AGE is negatively related to the LOG_ANNW. They are all statistically significant (p=0.00). The LOT and the ASSESS variables are relatively strong indicators in terms of t-statistics. A positive sign of LOT coefficient suggest that the single family household living in a large size of lot tends to consume more water than a similar household in a smaller lot when other conditions are held at fixed values.

Table 28: Results for Annual Water Use Volume in OLS Model

Dependent: Log of Annual Water Use in gallon (LOG_ANNW)		Unstandardized Coefficients		t-statistics	Probability
		B	Std. Error		
Independent	Constant	10.783	0.029515	365.3362	0.000**
	Lot size in acre (LOT)	0.149767	0.015252	9.819236	0.000**
	Assessed value (ASSESS)	1.37E-06	2.43E-08	56.35322	0.000**
	Structure year since 1950 (AGE)	-0.00178	0.0007	-2.54654	0.011**
	Structure floors (FLOOR)	0.057716	0.010742	5.372791	0.000**

Because this is a log-level model (*log(y)* as dependent *with x* as independent), the *b* = 0.149 gives the interpretation that one-unit (1 acre) increase of lot size in single family household will result in about 16.15 percent increase in annual water use when the other conditions are equal, since Exp[0.149 * 1] = 1.16156. This suggests that residential development patterns in favor of a large size of lot associated with non-compact development pattern or sprawl is likely to result in an increase in water use.

The indicators associated with affluence level of household, such as assessed property value (ASSESS) serving as a proxy of household income and the structure floor (FLOOR), also suggest that richer households would consume more water than others when other conditions are fixed. The negative sign of structure year (AGE) implies that the volume of water consumed in old buildings is likely to be higher than that of newly constructed buildings when the other conditions are the same. This would suggest that newer houses have been built with more efficient water-using devices.

RESULTS FOR THE SPATIAL ERROR MODEL

Diagnostics for spatial dependence and results for the spatial error model

Back in Figure 20, Moran's I, Lagrange Multiplier (lag model, error model, and SARMA), and Robust LM (error and lag model) showed the results of assessment related to the spatial dependence of the model. First, positive value of Moran's I score of 0.0519 ($p = 0.00$) indicates existence of spatial autocorrelation of the residuals in the model. The remaining statistics, LM test for a missing spatially lagged dependent variable (LM lag), error dependence (LM error), variants of these robust to the presence of the other (Robust LM –lag and error), and portmanteau test (SARMA), are consistently significant, indicating present of spatial dependence. The robust tests results typically suggest what type of spatial dependence is at present. Both spatial lag model and spatial error model can be tested as all LMs and Robust LMs test statistics results were significant; however, only spatial error model (SEM) was considered valid design in this study.

After identifying the presence of spatial dependence, this study has rerun the model with maximum likelihood approach while controlling for the spatial dependence. Figure 21 and Table 29 show the results from spatial error model, where a coefficient on the spatially correlated errors (LAMBDA) has been added. Because the LAMBDA was 0.762 (positive) and highly significant, the general model fit improved. R-squared and Log likelihood value were higher than a simple OLS (R^2 = 0.304, Log likelihood = -12351.1). The effects of other independent variables remain the same in terms of signs of coefficient estimates.

```
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Dependent Variable  :  LN_ANN_GAL  Number of Observations: 15594
Mean dependent var  :   11.349435  Number of Variables   :     5
S.D. dependent var  :    0.637480  Degrees of Freedom    : 15589
Lag coeff. (Lambda) :    0.762984

R-squared           :    0.304306  R-squared (BUSE)      : -
Sq. Correlation     : -            Log likelihood        :-12351.195712
Sigma-square        :    0.282716  Akaike info criterion :     24712.4
S.E of regression   :    0.531711  Schwarz criterion     :     24750.7

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS TEST                 DF       VALUE        PROB
Breusch-Pagan test                       4       440.2682     0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
TEST                                     DF       VALUE        PROB
Likelihood Ratio Test                    1       727.8228     0.00000
```

Figure 21: Summary of Output: Parcel-Level Analysis - Spatial Error Model

Coefficients estimates and their interpretations

Table 29 summarizes the results for the coefficients in the SEM. All independent variables, the lot size (LOT), the assessed value (ASSESS), and the structure floor (FLOOR) variables are significant predictors in the model. The result also shows that the signs of coefficients of the independent variables are the same as in the result from the OLS model. All independent variables (LOT, ASSESS, and FLOOR) except AGE variable positively correlates to the logged annual water use variable (LOG_ANNW).

Table 29: Results for Annual Water Use Volume in Spatial Error Model

Model: Spatial Error Model Dependent: Logarithm of Annual Water Use in gallon		Unstandardized Coefficients		z-value	Probability
		B	Std. Error		
Independent Variables	Constant	10.94506	0.04900092	223.3643	0.000**
	Lot size in acre (LOT)	0.09546904	0.0175009	5.455094	0.000**
	Assessed value (ASSESS)	1.02E-06	3.77E-08	27.18061	0.000**
	Structure year since1950 (AGE)	-0.0031069	0.001123549	-2.765259	0.006**
	Structure floor (FLOOR)	0.07846719	0.01147391	6.83875	0.000**
	LAMBDA	0.7629839	0.02034371	37.50466	0.000**

Background variables: ASSESS, AGE and FLOOR Variables

The coefficients (*b*i) for ASSESS, AGE, and FLOOR in the SEM is estimated to be 1.02E-06, -0.0031069, and 0.07846719. Since the dependent variable in SEM is log-transformed, each exponentiated coefficient *b* [Exp (*b*)] represents the change in the ratio of the expected geometric means of the original outcome variable. Specifically, when the assessed value increases by $1,000, we expect to see 0.1 percent increase in annual water use per household when other predictor variables at any fixed value since Exp [1.02E-06 * 1000] = 1.00102. For AGE variable, one-unit decrease means that a structure is one year older than others. Hence, we can expect 0.31 percent increase in annual water use per each one-unit decrease in AGE (one additional year of house age) since Exp [-0.003106 * (-1)] = 1.003112. For FLOOR variable we can expect 8.16 percent increase in annual water use for every one-unit increase in FLOOR, holding other values constant since Exp [0.07846719 * 1] = 1.081628

Policy control variable: LOT variable

For LOT variable, we can expect 10.02 percent increase in annual water use when one unit (1 acre) increase in lot size since Exp [0.09546904 * 1] = 1.100175. However, with realistic, the average lot size of a single family housing residential in the sample dataset in the analysis is 0.4 acre, which is smaller than an acre.

Table 30 presents the expected percentage changes in annual water use per households corresponding to decrease of lot size. In SEM model when lot size is reduced by 0.1 acres, 0.2 acres, and 0.5 acres with realistic, we expect to see about 0.95 percent, 1.89 percent, and 4.66 percent reduction in annual water use per household respectively when all other variables hold with fixed values.

Table 30. Percent Change in Annual Water Use – SEM Model

Model	Coefficient (*b*)	Lot size Change(Acre): decrease (Δ)	Ratio of the expected means of annual water use [Exp(*b* *Δ)]	Percent Change in Annual Water Use [Exp(*b* *Δ)] - 1
Spatial Error Model	0.095469	-0.10	0.9905	-0.95%
		-0.20	0.9811	-1.89%
		-0.50	0.9534	-4.66%

DISCUSSIONS FOR POLICY IMPLIATIONS

EVALUATION FOR MODEL SPECIFICATIONS AND MEAN OF WATER USE

Mean of annual water use per household and daily per capita water use rate

As shown above in Table 26, the mean of annual water use per household (or per account) in this study is calculated as 105,733 gallons. This is equivalent to 8,811

(=105,733 / 12) gallons per month per household or 289.68 (= 105,733 / 365) gallons per day per household. Since the average household size of Fulton county in 2010 is 2.36 (US. Census Bureau, 2010 Census), the average water use in gallon per capita per day (GPCD) is approximately calculated to be 122.75 (= 289.68 / 2.36).

According to the 'Water Supply and Water conservation management plan' report published by Metropolitan North Georgia Water Planning District (MNGWPD, hereafter) in 2009, the gallon per capita per day (GPCD) of single family residential in Fulton county in 2005 was estimated to 106 (indoor= 79 and outdoor = 28), which is 16 percent lower than the average value of GPCD calculated in this study. But the affluence level of the study area, north Fulton county area, is higher than that of the county as a whole; hence, average water use per household in three cities would be higher than the average of water use per household in Fulton County as a whole. Therefore, the result of the mean estimate in this analysis is a reasonable representation of the real volume of single family household water use rate.

OLS Model vs. Spatial Error Model

When comparing a spatial regression model (Spatial Error model) to a simple OLS models, the spatial error regression models improved the model fit substantially. In theory, the error term captures all unknown and unincorporated influences including spatial autocorrelation on the dependent variable in spatial error model. Therefore, this study confirmed that the SEM is a more appropriate model configuration than the OLS model to examine the relationship between the predictors (LOT, ASSESS, FLOOR, AGE) and the outcome variable, water use (LOG_ANNW).

In the results, the spatial error model still shows a consistent relationship in terms of +/- signs for coefficients between the annual water use volume and the four independent variables. However, comparing to OLS model, the coefficients of the predictors in SEM become lower than in the OLS model. Especially the coefficients for LOT is changed from 0.14 to 0.095. In the SEM, the influence of lot size on annual water use is diminished while the error terms were able to capture the unknown and unincorporated factors. Regardless of these change, the result still support an argument that smaller lot size is favorable to sustainable water use through achieving water reduction. Then, what is the actual water use savings associated with reduction in lot size? Would reducing lot size lead to sustainable water use effectively?

POTENTIAL OF THE LAND USE APPROACH IN SUSTAINABLE WATER USE

One of the arguments of this study is that compact urban growth policy can play an important role in water use reduction and should continuously be coupled with sustainable water use policy in urban areas. Especially, in this study design, lot size associated with residential density is proposed as a policy control variable. The results suggest that when other conditions are equal or hold status quo a single family residential with a smaller lot size would consume less water annually. Then how much less?

Let's assume Fulton County were to consider promoting compact growth policy and recommend zoning regulation changes regarding a typical single family lot size. As shown previously in Table 26 and the average lot size was 0.4 acre. In terms of density this is equivalent to 2.5 (= 1 / 0.4) housing unit per acre (HU/Acre, hereafter). When the lot size is reduced by 0.1 acre and 0.2 acre, the density becomes 3.3 HU/Acre (= 1/ (0.4-

0.1)) and 5 HU/Acre (= 1/ (0.4-0.2)) respectively, which are equivalent to approximately 33 percent and 100 percent increase from the mean lot size.

When lot size is reduced by 0.1 acres and 0.2 acres, according to the analysis results in Table 30, water use falls by 0.95 percent and 1.89 percent, respectively. If we convert this change to actual volume of annual water use using the mean annual water use, 105,733 gallons per household, actual water savings would be 1,005 gallons per year per household and 2,000 gallons per year per household (Table 31). As the Fulton County average household size is 2.45 person per household, the daily savings per capita value are calculated as 1.14 (=1,005 / 365 / 2.45) gallons per person per day for 33 percent single family density increase and 2.24 (=2,000 / 365 / 2.45) gallons per person per day for 100 percent single family residential density increase through lot size change. (Table 31).

Table 31. Water Savings Potential by Lot Size Reduction: SEM Model

Lot size Change (Acre): decrease (a)	Density Change From the average lot size (b)	Percent Change in Annual Water Use (c)	Estimated Annual Water Use Savings per account in gallons (d) = 105,733 × (c)	Estimated Daily Water Use Savings per account in gallons (e) =(d) / 365	Estimated Daily Water Use Savings per capita in gallons (f) = (e) / 2.45
-0.10	+ 33%	-0.95%	-1,005	-2.8	-1.14
-0.20	+ 100%	-1.89%	-2,000	-5.5	-2.24

Note:
(1) Average lot size = 0.4 acre; (2) Mean annual water use =105,733 gallons; (3) Average household size in Fulton County = 2.45.

According to MNGWPD water report (2009), the Fulton County single family outdoor GPCD was an estimated 28 gallons. Fulton would have to increase typical residential density by 33 percent to reduce the daily outdoor water use rate from 28 gallons to 26.9 gallons. Even doubling the current single family residential density (100 percent increase) would result in shifting 28 gallons per day to only 25.8 gallons per day.

When comparing to other conservation measures related to outdoor water use, magnitude of the effect of water use reduction by land use approach is very modest, not as effective as technological approach such as irrigation scheduling or xeriscaping (landscape design) for sustainable water use management. Several studies quantify the effects of proper management on these approach. For example, the study in North Marin Water District in California, it was found that the proper choice of plants and careful landscape design (xeriscaping) could reduce water use by up to 54 percent (Nelson 1994). Also, Sovocool (2005) suggests that switching from turf grass to xeriscaping would reduce water use from 73 gallons per square feet annually to 17.2 gallons per square feet per year (55.8 gallons per square foot annually or 1.5 gallons per square feet at a minimum during the winter months and 9.6 gallons per square feet at a maximum during the summer months (Figure 22) (Sovocool 2005). In this study, the effect of lot size reduction by 0.1 acre (or 4356 square feet) is calculated as 0.23 gallons per square feet per year (= 1,005 gallons / 0.1 acre * 1/43560 acre/feet), which is not as effective as xeriscaping as discussed in Sovocool's study.

Nevertheless, it should also be acknowledged that most counties in Metro Atlanta area including Fulton County is expected to see its population increase by more than 2 million over the next 30 years. If it is assumed that approximately 70 percent of the new population lives in single family housing in the future, reducing lot size by 0.1 acre can achieve approximately 1.16 million gallons per day saving (= 2 million * 0.7 * 1.14 gallon per day) by 2040, which could be also substantial or even critical amount during a drought season. When considering limited availability in water resource in the Atlanta Metro region and past water drought histories, the effectiveness of water savings by compact growth policy is still a valuable planning alternative that local planning and water management authorities should positively considered in sustainable water use management framework.

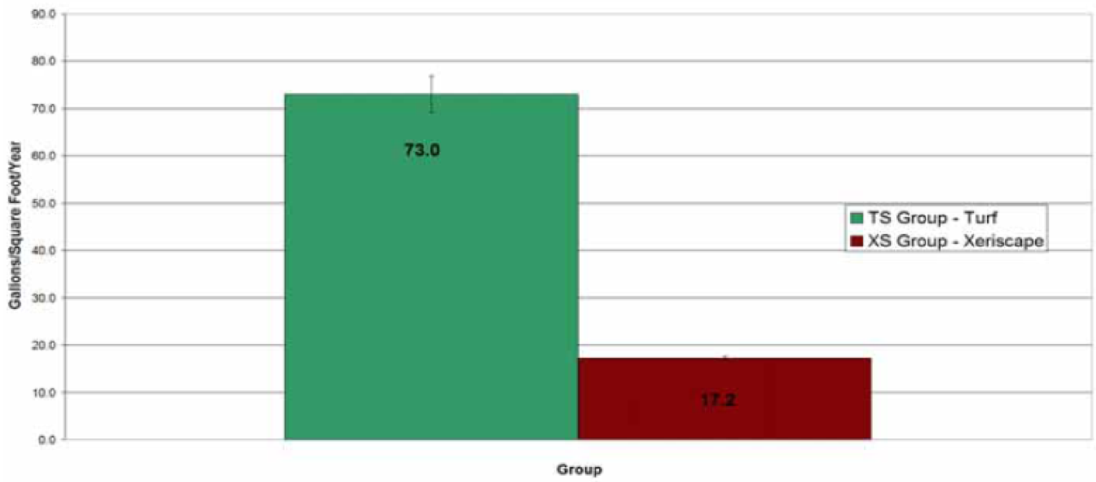


Figure 22. Water Savings by Xeriscaping (Sovocool, 2005)

LIMITATION OF STUDY DESIGN AND FUTURE DIRECTION

A couple of limitation in the analysis design needs to be acknowledged. First, because the geographic scope in the parcel-level analysis is limited to three cities of Fulton County, GA, and thus may not be generalizable to other regions with different climates and built environments. Second, the sample set in the regression analysis did not include any other uses than single family residential parcels and its water use data. In order to discuss urban residential water use or urban water use, other types of parcels should be included in order to discuss the urban density and urban water use.

Third, data resource constraints in various types of explanatory variables in water consumption were a major challenge in the research design. In particular, the analysis lacked detailed socioeconomic data and building structure information. There remains a great deal of uncertainty about residential behavior and water consumption. Future extension of this research would be to gather data on diverse spatial explanatory variables, such as lawn size and the presence of outdoor pools, and socio-economic variables of interest such as income at household level, a number of family member, local water price.

Fourth, this study assumed that the magnitude of water use change by lot size change is interpreted as an annual per capita outdoor water use. However, most outdoor water is consumed in spring and summer, rather than equally distributed over a year. Therefore, the analysis for seasonal water consumption of April, May, June, and July ONLY would also suggest meaningful policy implications. In this study, due to inconsistent water billing periods, the water consumption data has to be aggregated to total annual usage values. Besides, planning for surges in water use and changes in seasonal rainfall averages, including droughts, are a high priority and concerns when devising sustainable water use management plan for many arid cities in the US. Therefore, similar studies in future would be improved with access to water consumption data at a daily or monthly level.

CHAPTER SUMMARY

This chapter examined the relationship between single family housing lot size and annual water use at household level in four cities in Fulton County, GA. To test this relationship, OLS and SEM regression models were run. In terms of model validity, SEM is a more appropriate model than OLS in examining coefficients and relationships among variables because it resolves the spatial autocorrelation issue that threatens the validity of simple OLS models.

All predictors of the lot size, the assessed value of parcels, and the number of stories of residential building are all positively correlated with the dependent variable of volume of annual water use. Building age is negatively correlated with annual water use. The analysis results suggest that a smaller lot size would contribute to reduction of per-capita water use in single-family housing; however its magnitude is vey modest. When lot size is reduced by 0.1 acre, we can expect approximately 0.95 percent of annual water use, holding all other values constant. Such reduction is equivalent to 1,001 gallons per household per year or approximately 1 gallon per capita per day savings. Because the average lot size for the study area is 0.4 acres, changing from the average lot size of 0.4 to 0.3 acre requires housing unit density increase by 33 percent. Therefore, local government may expect achieving 1 gallon per capita per day (GPCD) saving when they change typical single family lot size from 0.4 acre to 0.3 acre (33 percent increase in single family housing unit density).

It is important to acknowledge that the magnitude of the effect of single family residential density increase on annual volume of water consumption is not as much as other outdoor conservation measures such as xeriscaping. Therefore, sustainable water use management should also embrace various policies related to conservation measure improvement through technological solutions while promoting compact urban growth policies in the sustainable water use management framework.

CHAPTER 5

LONG-TERM SUSTAINABLE WATER DEMAND AND ESTABLISHING CONSERVATION SCENARIOS

In chapter 2, this dissertation reviewed literature discussing the sectoral approach for measuring urban water use, long term urban water demand forecasting methods, and water conservation measures, including rainwater harvesting. Although such studies provide us with an overall understanding of how urban water use can be disaggregated by user groups and how each sectoral water demand can be calculated at aggregated group level, there are always local variations in water use profiles. In chapter 3 and chapter 4, the analysis showed how water use might vary with spatial variables, including residential lot size. Therefore, estimates of future water use should take into account the local profile, including climate and land-use patterns. Such information should be collected, reviewed, discussed in order to establish planning alternatives that reflects reasonable ranges of water use rate changes to achieve sustainable water use management goals.

This chapter discusses how local government and water-use planning authorities can develop locally specific long-term water-use scenarios and plan for more sustainable water use. The case of metropolitan Atlanta area will be discussed as a sample study.

The goal of this chapter is to develop multiple scenarios, including a desirable sustainable water use case, which will be applied to the case study in the following Chapter 6. One of the main research objectives is to develop a GIS-based water demand forecasting application with representative water coefficients and conservation scenarios. Hence, the scenarios are established with conventional methods in demand forecasting, which are (1) sectoral approach or end use unit approach, and (2) water conservation and scenario-based approach. The scenarios developed in this chapter are incorporated to the analysis framework of the 'Sustainable Water use Scenario-based Planning Support Systems (SWSPSS). The final set of scenarios are proposed in the end of this chapter.

RESEARCH DESIGN

DEVELOPMENT OF FUTURE SCENARIOS FOR SWSPSS APPLICATION.

This section endeavors to develop different scenarios of urban growth and conservation scenarios for sustainable water use. As planners should be able to consider possible outcomes from uncertainty or multiple path ways in the future, 'scenario-based approach' is commonly employed by planners to develop alternative plans for assisting decision making (Hopkins and Zapata 2007). Scenario-based approach is used not only in water demand forecasting but also in planning practice. In general, a scenario reflects a set of plausible alternatives to be analyzed with logical process and reasonable assumptions. When examining alternative plans, scenarios can be set to answer the questions of "what might happen or generate impact on communities if incidents or policy actions occur during certain period of time" (Hopkins and Zapata 2007).

This dissertation study assumes that sustainable developments that combines urban development configuration (land use) approach and technological conservation effort would alter the individual representative daily per capita water use coefficients. These representative coefficients are obtained from local water district reports, literature.

The conceptual diagram in Figure 23 shows how urban development configuration (land use) approach and technological approaches in sustainable water use assumptions affect unit-demand changes (per capita, per employees, or per square footage of buildings) in both residential and non-residential water use.

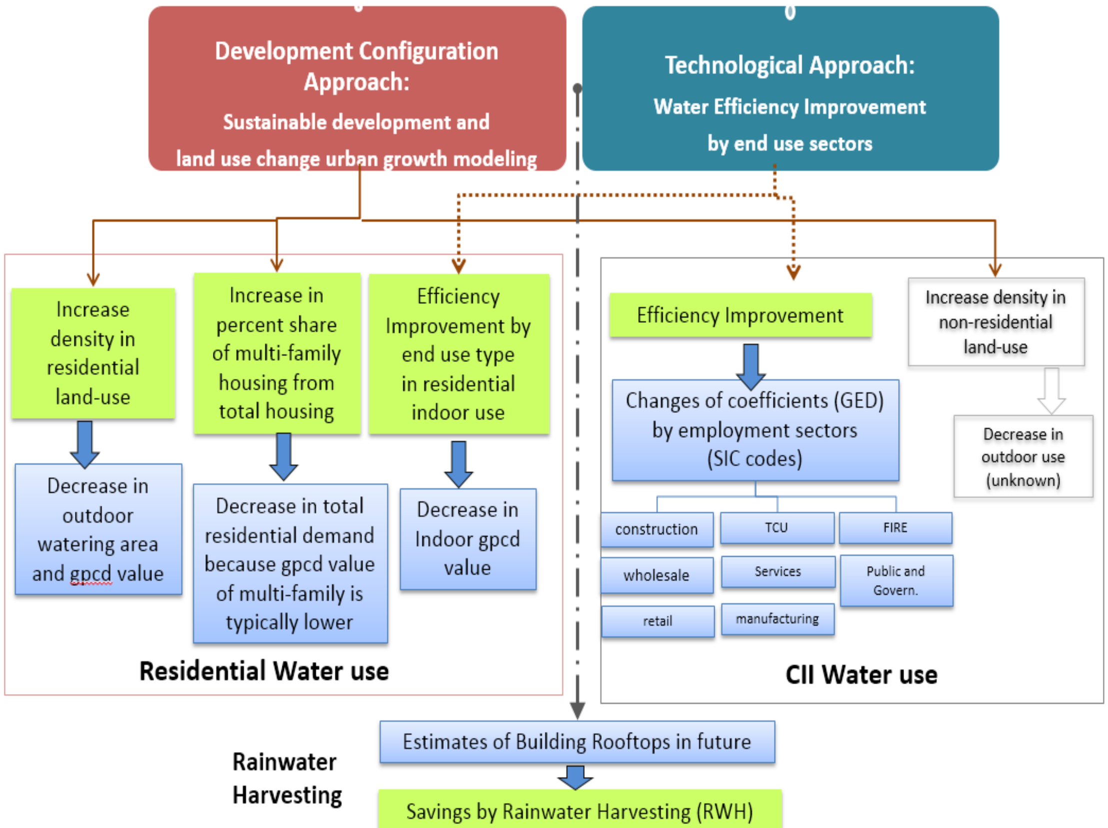


Figure 23: The Land Use-Development Configuration Approach and the Technological Solutions Approach in Scenario Development

To contrast the outcome of different growth policies, this study developed several different development scenarios for the future trend analysis: the case of business-as-Usual (BAU, hereafter) (Scenario A), the case of the sustainable development (SD, hereafter) (Scenario B), and the case of SD with RWH scenario (Scenario C). In essence, the SD scenario is different from the BAU in terms of three perspectives:

(1) Substantial increase in residential and employment density in the SD;

(2) Higher percentage of multi-family housing share in future development

(3) Reduction in representative water use coefficients -GPCD (gallon per capita per day) and GED (gallon per employment per day).

Based on this conceptual approach, major assumptions and descriptions of each scenario are summarized in Table 37 at the end of this chapter.

Based on the literature review and local water reports, this study attempts to test multiple scenarios composed of a series of ‘what-if’ assumptions. The geographic scope of this study includes thirteen counties in metropolitan Atlanta, Georgia (Figure 24).

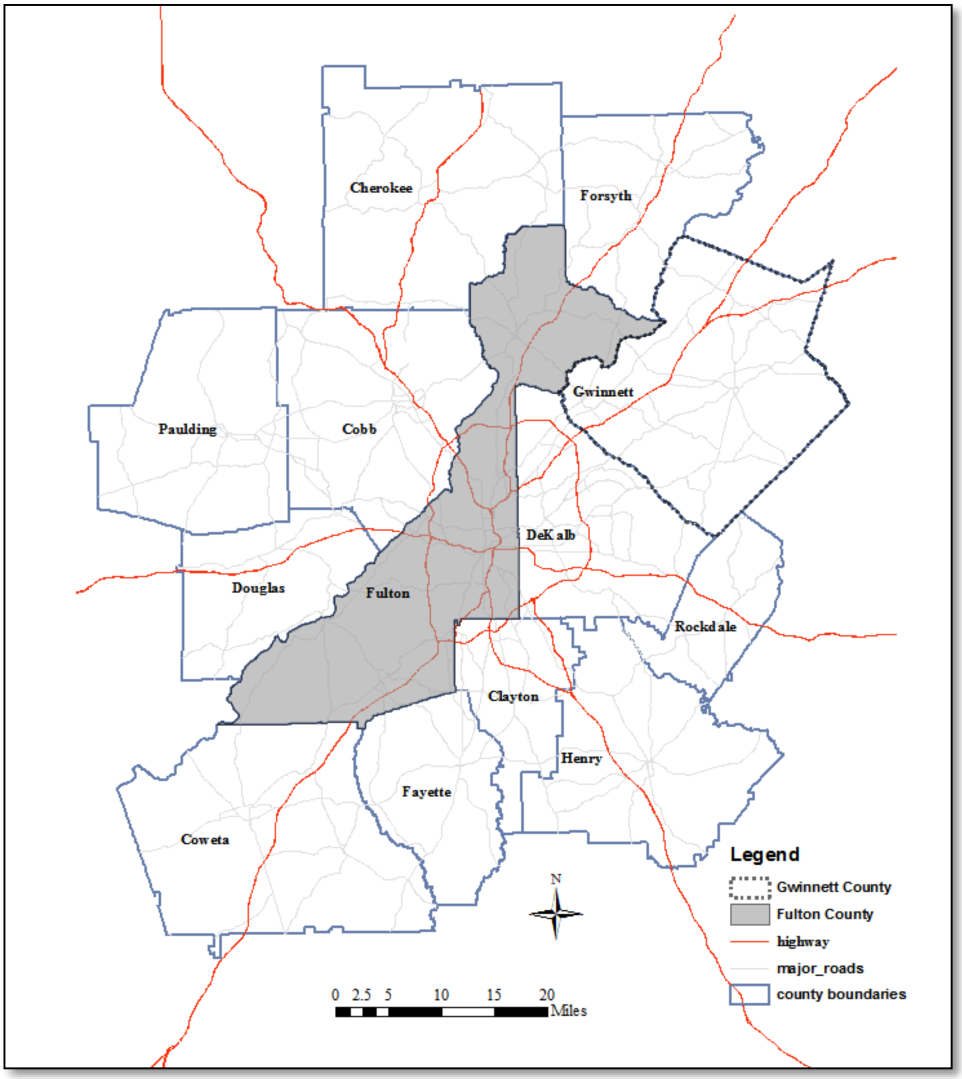


Figure 24: A Study Region: Thirteen Counties in Metropolitan Atlanta, Georgia (RWH analysis Area in Gray)

<u>Land use approach and urban growth assumptions</u>

In the BAU scenario, residential density, employment density, and infill rates are determined from reviewing Atlanta Regional Commission land use classifications, US census data, and literature. For residential uses of single family residential and multi-family residential (SFR and MFR hereafter), five urban core counties (Clayton, Cobb, DeKalb, Gwinnett, and Fulton) have higher density values and infill rates than the rest counties. For employment uses, the density values from the Nelson's study (2004) were adopted for this study case (Nelson 2004). In the SD scenario, residential and employment densities for new developments were increased from the BAU assumptions. The percentage of single family housing is decreased by 20 percent for new development in the SD. Infill rates are also increased by 10 percent. Table 32, 33, and 34 summarize the difference between two growth scenarios. They show the density changes in each county for the residential land uses and employment land uses.

Table 32: Residential Density for BAU and SD Scenarios

<table>
<tr><th colspan="2" rowspan="2">County</th><th colspan="3">Base year 2010</th><th colspan="2">BAU scenario</th><th colspan="2">Sustainable Development Scenario</th></tr>
<tr><th>Average household size</th><th>Density of single family units</th><th>Density of multi-family units</th><th>Density of single family units</th><th>Density of multi-family units</th><th>Density of single family units</th><th>Density of multi-family units</th></tr>
<tr><td rowspan="5">5 Core counties</td><td>Clayton</td><td>2.86</td><td rowspan="13">1/4 ~ 4 HU/acre* or 1/3 ~ 10 HU/HA</td><td rowspan="13">> 8 HU/acre* or > 20 HU/HA</td><td rowspan="5">3 HU / acre or 7.5 HU/HA</td><td rowspan="5">10 HU / acre or 25 HU/HA</td><td rowspan="5">6 HU / acre or 15 HU/HA</td><td rowspan="5">16 HU / acre or 40 HU/HA</td></tr>
<tr><td>Cobb</td><td>2.65</td></tr>
<tr><td>DeKalb</td><td>2.55</td></tr>
<tr><td>Fulton</td><td>2.45</td></tr>
<tr><td>Gwinnett</td><td>3.0</td></tr>
<tr><td rowspan="8">Suburban rural counties</td><td>Cherokee</td><td>2.82</td><td rowspan="8">2 HU / acre or 5 HU/HA</td><td rowspan="8">8 HU / acre or 20 HU/HA</td><td rowspan="8">4 HU / acre or 10 HU/HA</td><td rowspan="8">12 HU / acre or 30 HU/HA</td></tr>
<tr><td>Coweta</td><td>2.79</td></tr>
<tr><td>Douglas</td><td>2.84</td></tr>
<tr><td>Fayette</td><td>2.79</td></tr>
<tr><td>Forsyth</td><td>2.95</td></tr>
<tr><td>Henry</td><td>2.9</td></tr>
<tr><td>Paulding</td><td>2.96</td></tr>
<tr><td>Rockdale</td><td>2.84</td></tr>
</table>

Source*: Atlanta Regional Commission, LandPro LULC Classification System

Table 33: Configuration of Single Family and Multi-family Housing in Scenarios

	Base year 2010 (ARC estimates)		BAU scenario			Sustainable Development Scenario		
County (*=core co.)	Percent of single family units (mobile H. Incl.)	Percent of multi-family units	Percent of single family units for forecasting	Percent of multifamily units for forecasting	Infill rate	Percent of single family units	Percent of multifamily units	Infill rate
Cherokee	88.2%	11.8%	90%	10%	20%	70%	30%	30%
Clayton*	69.5%	30.5%	70%	30%	20%	50%	50%	30%
Cobb*	72.6%	27.4%	70%	30%	20%	50%	50%	30%
Coweta	90.8%	9.2%	90%	10%	20%	70%	30%	30%
DeKalb*	61.3%	38.7%	60%	40%	20%	40%	60%	30%
Douglas	87.0%	13.0%	90%	10%	20%	70%	30%	30%
Fayette	92.0%	8.0%	90%	10%	20%	70%	30%	30%
Forsyth	95.0%	5.0%	90%	10%	20%	70%	30%	30%
Fulton*	54.8%	45.2%	60%	40%	20%	40%	60%	30%
Gwinnett*	78.9%	21.1%	80%	20%	20%	60%	40%	30%
Henry	90.5%	9.5%	90%	10%	20%	70%	30%	30%
Paulding	94.2%	5.8%	90%	10%	20%	70%	30%	30%
Rockdale	87.2%	12.8%	90%	10%	20%	70%	30%	30%

Table 34: Employment Density for BAU and Sustainable Development Scenarios

Land use type	employment density for BAU (employee/acre)	employment density for SD (employee/acre)
Construction	28.73	43.10
Manufacturing	16.44	24.66
TCU	29.88	44.82
Wholesale Trade	16.22	24.33
Retail Trade	16.62	24.93
FIRE	31.08	46.62
Services	31.08	46.62
Public Administration	31.08	46.62

Source: Arthur Nelson, 2004, Planners' estimating guide 2004. APA press

<u>The water use scenario in BAU and SD</u>

In order to understand a local water use profile, this study obtained a list of GPCDs and GEDs from local water planning authority reports and literature. For residential use, each county's GPCDs of single family and multifamily uses were obtained from the water report published by North Georgia Metropolitan Water District

(MNGWD, 2009). The report provides a list of gallon per capita per day values of single family and multi-family residential indoor use and outdoor use by county. For non-residential subsectors, GEDs were obtained from parameters from Dziegieleski et al (Dziegielewski and Boland 1989) (Table 36).

In estimating conservation savings, a typical example of methodological approach is shown in Rodrigo's work (Rodrigo 1990). Rodrigo (1990) suggested that water conservation savings can be estimated in simple equation as below.

$$\boldsymbol{S_{i,j} = Q_j * R_{i,j} * C_{i,j}}$$ **…………….. Equation 4** (Rodrigo, 1990)

Where: $S_{i,j}$ = conservation savings for conservation measure *i*, affecting water use sector *j*

Q_j = base use without conservation water use in sector *j*:

R_{ij} = percent reduction from conservation measure *i* affecting sector *j*

C_{ij} = coverage associated with the conservation measure *i* in sector *j*

However, estimating S_{ij} can be a fairly complicated procedure. The coverage factor C_{ij} requires extensive knowledge of each conservation measure for each sector and the service areas. Often advanced statistical procedures are used to estimate R and C; however, long-range savings can be estimated when using actual water use data which is disaggregated by user classes (such as residential, commercial, and industrial), as well as factoring in seasonal water use profiles for indoor and outdoor use, and potential water savings by individual device or conservation measures.

In this study, the BAU scenario assumes that there is no change in GPCDs and GEDs in future water use. The SD scenario assumes that the impact of conservation measures in the future would achieve significant water savings not only by development configuration changes (density and percentage of SFR) but also by improvement of water efficiency. As a result, the SD is attributed to 20 percent reduction in residential water use in terms of GPCD and GED for new demand in future. Residential reduction ratio is decided based on indoor reduction rate by EPA WaterSense guideline for new single family construction (EPA 2009), which suggests that a per capita daily water use for typical single family home can be dropped from 49.8 GPCD to 39.5 GPCD (20.7 percent savings) when new WaterSense standard is enforced. As discussed in the literature review, non-residential sector conservation measures and its ranges are hard to determine, although most efficiency measures were within 21 percent to 50 percent. This dissertation study assumed an efficiency improvement of 20 percent in the new development structures.

Table 35: Modified Residential Water Use Coefficient in the BAU and SD Scenario

County		Single Family Residential GPCD		Multi-family residential GPCD	
	Efficiency ratio applied	BAU	SD	BAU	SD
Cherokee	20.7 percent reduction in GPCD	79	63.2	69	55.2
Clayton		81	64.8	78	62.4
Cobb		82	65.6	67	53.6
Coweta		83	66.4	67	53.6
DeKalb		85	68.0	69	55.2
Douglas		78	62.4	60	48
Fayette		87	69.6	63	50.4
Forsyth		99	79.2	67	53.6
Fulton		106	84.8	83	66.4
Gwinnett		91	72.8	67	53.6
Henry		78	62.4	69	55.2
Paulding		80	64.0	72	57.6
Rockdale		83	66.4	71	56.8

Table 35 and Table 36 summarize the water coefficients applied for the new development in residential and non-residential uses in two sustainable scenarios, the BAU and the SD. In addition, population and employees residing in pre-2010 base year also expect to have a 10 percent reduction in GPCDs and GEDs as conservation measure improvement as shown in the scenario summary table (Table37) at the end of this chapter.

Table 36: Modified Employment Water Use Coefficient in the BAU and SD Scenario

Employment Type	SIC Code	BAU (No change in GED coefficients*)	Sustainable Development (20 % of reduction In GED coefficients)
Construction	15-17	20.7*	16.56
Manufacturing	20-39	132.5*	119.25
Transport, communication, utilities (TCU)	40-49	49.3*	44.37
Wholesale trade	50-51	42.8*	38.52
Retail Trade	52-59	93.1*	83.79
Finance, insurance, real estate (FIRE)	60-67	70.8*	63.72
Services	70-89	137.5*	123.75
Public administration	91-97	105.7*	95.13

*source: Dziegieleswski and Boland, 1989

Sustainable water use scenario with rainwater harvesting (RWH)

Lastly, this study also consider rainwater harvesting (RWH, hereafter) by roofing areas for sustainable scenario because it potentially provide access to a reclaimed water source, although many potential, possibility of collecting and using rainwater has frequently been ignored (Angrill, Farreny et al. 2012). Rainwater can substitute water for the irrigation of farming, irrigation of gardens, the flushing of toilets, cleaning of road and outdoor surfaces, and other potential non-potable uses. Angrill et al (2012) found that rain water can be a competitive resource in urban areas with scare water resources.

This dissertation study incorporates RHW into water use scenario planning for several reasons. First, as the annual average precipitation level in Atlanta is moderately high when comparing to other states. In case of the metro Atlanta region, the average annual precipitation for last 30 years has been approximately 47 inches per year, which is close to or higher than national average. Therefore, RWH could be a viable option in the conservation policy. Second, hot summer weather and drought in the metropolitan Atlanta continuously stresses a supply of sustainable water use. Water collected from RWH can be used later to reduce shortage of water in peak demand and drought time. Third, RWH can reduce flash storm water runoffs in impervious surface areas. Forth, RWH is applicable to replenish the existing stock of many single-family housing units, which may collect more rainwater per unit than multi-family units because of relatively larger roof size.

In case of the state of Georgia, Georgia state's plumbing code 2009 - Georgia Amendments to the 2006 International Plumbing, Appendix I, "Rainwater Recycling systems"- allows rainwater to be collected, treated, and used indoors for toilet and urinal flushing and as cooling tower make-up water. In accordance with this amendment, Georgia Rainwater Harvesting Guidelines (2009) presented a simple estimate of the water harvested and a couple of case studies, which would be an important step in pursuing water conservation goals in Georgia (Affairs 2009). The report indicates RHW is still not economically preferable compared to the simple public water supply price and the cost of system installation in the short run; however, RWH would be a viable option when other benefits are considered, such as reduction in storm water runoff, the alleviated pressure of water shortage during drought season, low ecological impacts on natural systems, and the energy savings from reduced volume of water and wastewater treatment systems (Affairs 2009).

While developing a sustainable water use scenario, RWH can be considered as one of many planning policies for sustainable water use in long range. This study has attempted to estimate the maximum range of water savings through RWH, using GIS data of building footprints and regression models. The results show that substantial savings are possible when a series of assumptions are accepted. However, it should be acknowledged that there are substantial level of uncertainty in actual implementation of RWH policy in place in the study area the amount savings suggested

CHAPTER SUMMARY AND THREE SCENARIOS FOR SWSPSS

This chapter has elaborated how multiple scenarios are developed for the study area of thirteen counties in metropolitan Atlanta area. Three scenarios, BAU, SD, and SD with RWH, are discussed. Table 37 summarized and outlined the context of three scenarios in terms of two categories of approaches; (1) land use configuration changes and (2) water use profile changes. The previously demonstrated county-level analysis results suggested that the increase of density and decrease of single family housing percentage would contributed to reduction in county GPCDs. Therefore, regarding land-use configuration changes, sustainable water use scenario would need to include more compact development, and residential density and employment density values are increased accordingly.

For the case of water use profile changes, identifying conservation measures for different water use sectors are hard to determine precisely. Findings from the county-level analysis and parcel-level analysis suggest that compact growth would reduce water use rate. However, this dissertation does not attempt to estimate individual GPCD reduction ratios (or actual magnitude of reduction) by county to be exact. Rather, representative water use rates by county and by end user types are determined through local water use report and literature and incorporated to three scenarios. Finally, Table 37 presents the summary of three scenarios and main characteristics for two approaches.

In the following chapter, the three different scenarios—BAU, SD, and SD + RWH—are applied to metropolitan Atlanta to generate long-term water-use projections

Table 37. Summary of Three Scenarios

Scenarios	Urban development configuration Land use approach (urban growth modeling)	Technological approach (water efficiency)
Scenario A: BAU	▲ Low density development and sprawl continues ▲ Population/employment density in base year (2010) will be applied to future developments	▲ No substantial improvement in water efficiency for indoor use for future demand ▲ Coefficients of gallon per capital per day (GPCD) by county will remain the same
Scenario B: SD	▲Substantial increase in population/employment density for new development ▲Substantial decrease in percentage of low-density single family housing ▲Substantial reduction in residential outdoor use rate by smaller lot size	▲ 20% of reduction of GPCD (WaterSense – EPA-standard) is applied to new residential use and 20% of reduction in GED (gallon per employee per day) to CII (non-residential) sectors ▲ 10% of reduction of GPCD (WaterSense – EPA-standard) and GED (gallon per employee) is applied to pre-2010 existing (base year) population and employment sector users
Scenario C: SD + RWH	**Same as scenario B**	**= Same as Scenario B** + ▲ Rainwater harvesting (RWH) from residential and non-residential buildings

CHAPTER 6

DEVELOPMENT OF A SCENARIO-BASED PLANNING SUPPORT SYSTEM WITH SUSTAINABLE WATER USE SCENARIOS

This chapter discusses a GIS modeling framework and its usefulness in the context of a planning support system (PSS, hereafter) that would enable planners to project and easily compare the results of future urban water demand based on different scenario assumptions and parameters. This chapter produces a sample analysis to illustrate how the integrated land use-water model could be used in planning.

The GIS modeling framework introduced in this research shares substantial structural similarity with the existing planning support system '*What-if?*' developed by Klosterman (Klosterman 1999). The modeling framework in this analysis is composed of a series of simple and easily modifiable GIS modeling tools, interactive tabular datasets, and Python scripts in an ArcGIS environment (ESRI, 2015). This GIS framework is unique in that the system allows users to test both alternative urban growth and land use change scenarios and water efficiency improvement scenarios in a spatial context. This application can produce spatial layers of geographical water use distributions in the future based on different scenario inputs. Comparison of those alternatives enriches local sustainable water use policies and long-term water resource management planning actions. Thus the framework named Sustainable Water use Scenario-based Planning Support System (SWSPSS, hereafter), can be used in a variety of planning practices.

GIS, SPATIAL DECISION SUPPORT SYSTEMS, AND PLANNING SUPPORT SYSTEMS

The definitions of geographic information systems (GIS), spatial decision support systems (SDSS), and planning support systems (PSS), and their evolutionary path in planning disciplines have been discussed in many studies (Densham 1991, Harris and Batty 1993, Hopkins 1999, Klosterman 1999, Brail and Klosterman 2001, Geertman and Stillwell 2003). PSS is usually distinguished from GIS or SDSS (Geertman and Stillwell 2003). GIS is typically described as a general computer-aided system with a functionality of data collection and manipulation, spatial analysis, and visualization and display for a wide diversity of tasks and problem solving (Burrough 1986, Huxhold 1991, Goodchild 1992). The term SDSS, meanwhile, refers to systems designed to support a decision process for complex spatial problems based on the expert knowledge of decision-makers (Densham 1991, Geertman and Stillwell 2003) . In general, SDSS consist of database management systems with analytical models, graphical display, tabular reporting capabilities to support short-term policy making in decision making groups (Geertman and Stillwell 2003). SDSS commonly include GIS functionalities, spatial modeling and urban growth modeling capability at various spatial scales.

PSS, meanwhile, typically aims to support a particular or whole planning process by providing integrated environments (Brail and Klosterman 2001). Because planning practice deals with various spatial data, models, and tools, PSS often incorporates GIS and SDSS (Geertman and Stillwell 2003). PSS are distinguished from the other two for its particular utility for the planning profession (Geertman and Stillwell 2003).

Harris and Batty (1993) suggest a PSS combines a range of computer-based methods and models into an integrated system to be used in planning practices and to support a particular planning function (Harris and Batty 1993). They describe PSS as the framework with three components combined: (1) the specification of the planning task, problems, and data; (2) the system models and methods for analysis, prediction and prescription; (3) the transformation of data into information for modeling and design (Harris and Batty 1993).

Brail and Klosterman (2001) have extended the definition of PSS as information technologies used specifically by planners for their planning professions. They define the PSS framework as a combination of information, models, and visualization to be delivered to the public realm (Brail and Klosterman 2001). Klosterman (1997) elaborated how the role of PSS has evolved as the prevailing perspective of planning has changed, from applied science discussing urban models in the 1960s to political process in the 1970s, to communication in the 1980s and to 'collective design' in the 1990s, explaining how planning traditions and the role and usefulness of PSS have followed the intellectual discussion in planning discipline and evolved from simple tools adopting urban models into computer systems to more sophisticated communicative and consensus-building tools in planning practice (Klosterman 1997) .

However, Klosterman (1997) has also pointed out that a PSS is not comprised of GIS alone although GIS is an essential part of the PSS. He has suggested that desirable PSS should enable users to (1) select the appropriate analysis or forecasting tools, (2) link the appropriate analytic model to the information, (3) run the models to determine the implications of alternative policy choices and assumptions, and (4) view the results graphically (Klosterman 1997, Brail and Klosterman 2001).

The usefulness of PSS also depends on the implementation of present and future assumptions forming as scenarios for alternative policy review. Planners typically employ scenarios as alternative plans to test how incidents or policy actions would cause different outcomes. Various present and future assumptions can turn into hypothetical scenarios in the part of spatial analysis components in PSS. Then planners can examine the impacts or consequences, forecasting outcome from the different hypothetical scenarios to discuss more desirable and sustainable outcomes. By doing so, planners can provide 'useful' information to public realms and stakeholders so that they can engage in a specific planning process actively.

DEVELOPMENT OF PLANNING SUPPORT SYSTEM FOR WATER DEMAND FORECASTING IN LITERATURE

A PSS with the capacity to model urban growth and changes in land development could be used in water-use scenario planning because spatial patterns of population/employment distribution are closely related to land use types. Therefore, the ability to project future land use patterns should greatly improve users' ability to project future water use demand patterns spatially.

In water resource management planning, some studies have integrated the scenario-based approach into PSS (Gober, Wentz et al. 2011, Donkor, Mazzuchi et al. 2012, Wang, Burgess et al. 2012). The usefulness of adopting either PSS or GIS in urban water resource management and demand forecasting are also discussed (Panagopoulos, Bathrellos et al. 2012, Wang, Burgess et al. 2012). Panagopoulos et al. (2012) presented methods to seek and model major determinates of future growth of urban water demands of Mytilene, Greece. They showed how different thematic layers derived from GIS could be used to map out future water demand for the city. Specifically, they applied the AHP (analytic hierarchy process) (Saaty L 1977; Saaty, T. L. 1990; Marinoni 2004) in the evaluation of factors while spatially visualizing the potential water demand maps (Panagopoulos, Bathrellos et al. 2012). They concluded that the results of the AHP application, in combination with the GIS techniques, could be a useful tool for planners that assesses future water demand.

Wang et al. (2012) measured local water savings by multiple conservation options by implementing the commercially available software, CommunityViz (Wang, Burgess et al. 2012). In their study, they demonstrated how conservation scenarios could be developed based on water consumption characteristics per land use and possible climate change (temperature and precipitation). They calculated daily, monthly, and annual water use at the parcel level by using representative values of daily per capita indoor water consumption by land use types as the baseline. Then, conservation scenarios were applied based on the assumption of the combination of reduced daily per capita indoor water use by land use types and xeriscaping for outdoor use. They concluded that the model and systems they developed give citizens and decision makers a useful tool to make decisions about water consumption by exploring various conservation options and their impact on water consumption.

Gober et al. (2010) developed a scenario-based planning support system called WaterSim for Phoenix, Arizona (Gober, Wentz et al. 2011). It simulates how alternative climate conditions, population growth, and policy choices affect the future water supply and demand in the study area. The system includes four components: (1) exogenous uncertainties related to climate change and water supply variability; (2) policy levers associated with potential actions from decision makers; (3) a relationship that describes the equation and required variables; and (4) an outcome measure that shows water availability or ground water deficits. This structural system is built by adopting a system dynamic approach (stock and flow) to represent interactive relations among water supply and demand determinants. The system generated and compared potential outcomes for groundwater shortage and future water demand changes based on 'What if?' scenarios. The authors concluded that Phoenix's water supply would not suffice in the long run if the community's current business-as-usual condition continues.

RESEARCH MOTIVATION

Despite the volume of literature previously covering the applicability of PSS to water use management, not many studies connect land use change and water demand forecasting in the context of GIS-based integrated PSS with 'simple models' (Klosterman 2012) and easily customizable tools. Most GIS models and PSS linking land use changes to water resources focus on surface water quality (Tong and Chen 2002) and storm water management planning (Harbor 1994).

Models and a user interface embedded in a stand-alone hardwired PSS typically provide limited adaptability of models and input parameters. Therefore, this dissertation study attempts to develop a PSS that models and tools inside the PSS can be customized to project long-term water use demand with a spatial data base. This dissertation demonstrate how simple and easily modifiable tools are integrated and applied to generate spatial data representing future water use pattern at urban scale. This GIS modeling framework can be used as complementary tools in promoting sustainable water use planning.

RESEARCH DESIGN AND METHODS

INCORPORATION OF ANALYSIS CONCEPTS FROM 'WHAT IF?' AND 'CUF' INTO SWSPSS

This study proposes a scenario-based water demand forecasting framework or GIS model called 'sustainable water use scenario-based planning support system' (SWSPSS). It allows analysts to project and map out spatial pattern of long term water use. Local and regional water planning authorities can use SWSPSS to discuss more sustainable water demand options and implementation plans more effectively.

The GIS modeling framework for SWSPSS incorporates many of the design concepts in the PSS called 'What-if? '(Klosterman 1999) and the California Urban Futures (CUF) model (Landis 1995). What if? is a scenario-based policy-oriented planning support system that incorporates a series of GIS data to support community-based processes of collaborative planning and collective decision making (Klosterman 1999). The system allows user to conduct a series of analyses in *What if?* components of 'Suitability', 'Growth' and 'Allocation' that reflects the three aspects of the land use planning and development process: (1) land suitability analysis (Suitability); (2) land use demand analysis for future use (Growth); (3) and allocation analysis that allocates the projected demand to the most suitable locations (Allocation). In this dissertation study, the concept of three components, Suitability, Growth, and Allocation are incorporated into the SWSPSS design framework.

The California Urban Futures (CUF) is the forecasting and simulation models of urban growth patterns and the impacts of development policy at various levels of government (Landis 1995). The models allocate growth to sites based on development profitability and accessibility in the development process (Landis 1995, Landis 2001). The CUF model is built on two primary units of analysis, incorporated cities and the developable land units (DLUs). The DLU is a small size of land units in polygon representing status of undeveloped or developed areas that can be updated by policy changes. In this dissertation study the concept of DLU is also incorporated into the GIS analysis framework. The name of such land unit and the GIS polygon layer contains various attributes in this dissertation study is called land development grid unit (LDGU, hereafter) layer, which is also similar to the concept of UAZ in the What if? application (Klostorman 2001) .

Although this dissertation has incorporated several concepts from other PSSs, this study presents a new set of tools for integrating land-use scenario planning with water use estimations. Especially, this study demonstrates how Python scripting can be incorporated into the system so that users can conduct complex geoprocessing analysis in GIS easily.   Table 38 summarizes similarities and differences between What if? and the SWSPSS in this dissertation study.

Table 38. Comparison of SWSPSS and What if?

	What if ? (Klosterman, 1999)	SWSPSS
System overview	Stand-alone planning support system software Scenario-based policy testing Menu-driven user interface Graphical display and report generation capability	Loosely coupled system composed of python scripts, ModelBuilder models in ArcGIS (ESRI), and MS-Excel spreadsheets Suitability, land demand, allocation, and water use calculation modules A collection of tools/models in ArcGIS and MS-Excel
Development environment	Microsoft's Visual Basic and ESRI's MapObjects software	ModelBuilder models in ArcGIS (ESRI) Microsoft Excel Spreadsheet Python scripting and ArcPy module for geoprocessing
Suitability analysis	Suitability component in the system GIS vector overlay operation	Cell-based raster algebra operation using ModelBuilder models in ArcGIS
Land demand projection	Growth Assumptions component	Interactive Excel Spreadsheets
Allocation for land use projection	Allocation components in the system	Python Scripts in the allocation module
Water use calculation	Not applicable	Python scripts in the water use allocation module
Unit of analysis in spatial data	Uniform analysis zone (UAZ), typically in irregular shapes	Land development grid unit (LDGU) polygons (1 hectare square shape)
GIS Data type compatibility	Input: GIS vector layers in SHP format Output: GIS vector layers in SHP format; limited data type conversion capability	Input and output: SHP, Geodatabase (ESRI), Raster formats
Modification of input parameters and values	Typing in values through menus or component work sheets	Modifying values in list data or dictionary data in Python language

GEOGRAPHIC SCOPE OF STUDY

This dissertation study choose thirteen counties in the metropolitan Atlanta region, Georgia as a case study area (Figure 24, previously). The spatial extent of MSA Atlanta often refers to twenty three counties as of year 2009; however, this study has included only thirteen counties in Atlanta in order to maintain a consistency of geographical and temporal extent of GIS LULC datasets.

DEVELOPING THE SUSTAINABLE WATER USE SCENARIO BASED PLANNING SUPPORT SYSTEM (SWSPSS)

The SWSPSS is a composite modeling framework that combines the concept of deterministic or 'real-world process' urban growth models (Pettit 2005) and the sectoral water use forecasting techniques (Baumann, Boland et al. 1998) in accordance with user-defined future scenarios. The system is designed to examine the impact of alternative scenarios in both urban growth and local water use profile changes. It provides spatial data and graphical visualization for the future land use changes and water use increase in long run.

The system is essentially composed of several modules, GIS-based suitability module, land demand module, urban growth allocation module, and urban water use calculation module. The suitability module produces the composite land use scoring layers reflecting the probability to be developed or converted to other land use. The land demand module calculates future land demand for development. The urban growth allocation module produces future land use allocation GIS layers. The water use calculation module calculates the total water use demand increase in the analysis grid layer based on given water use profile assumptions and scenarios. Figure 25 and 26 present the components of modules and an analysis framework in detail. Notice the scenarios established in Chapter 5 are incorporated in the SWSPSS application analysis framework.

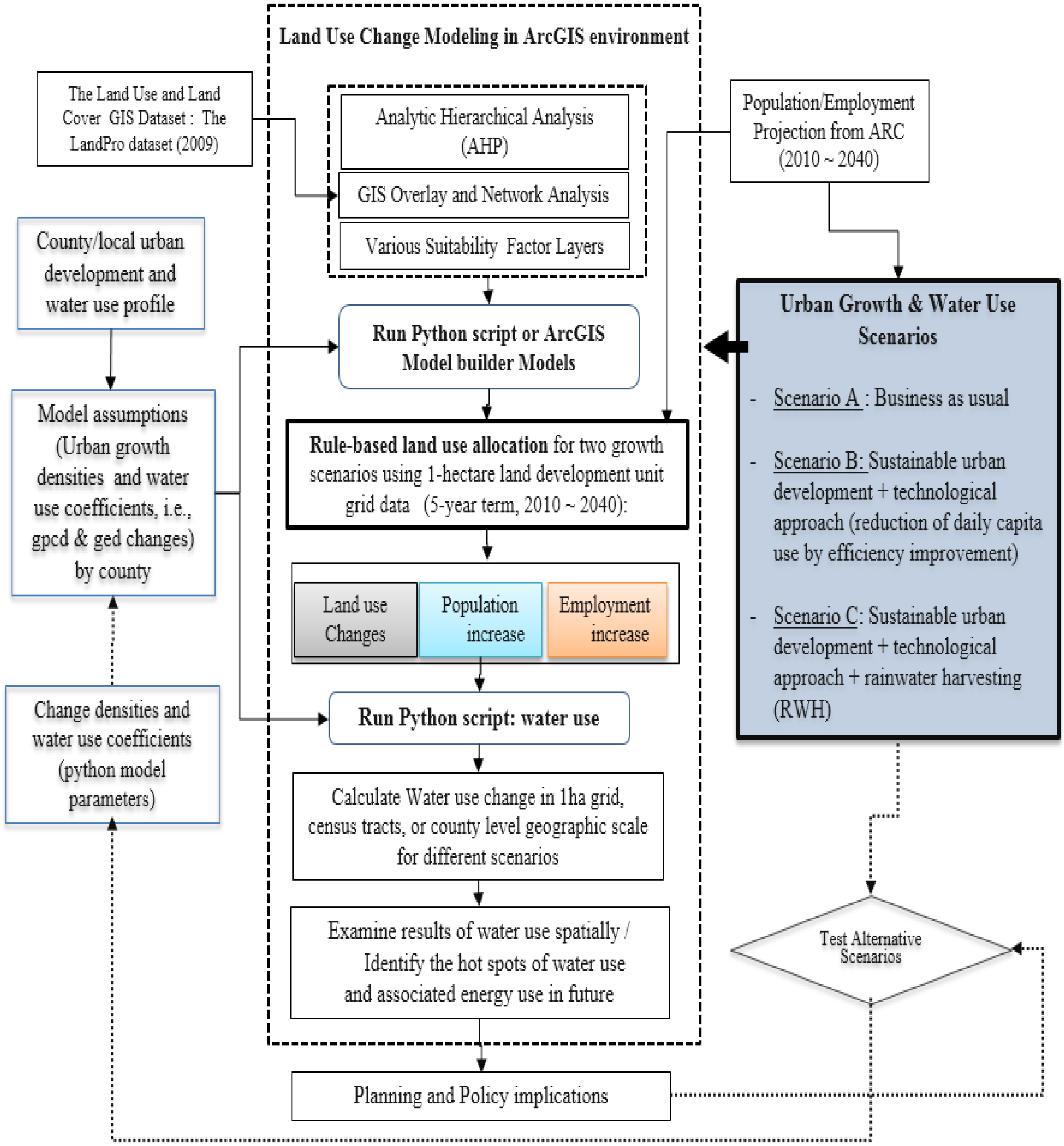


Figure 25: Analysis Flow and Framework of SWSPSS

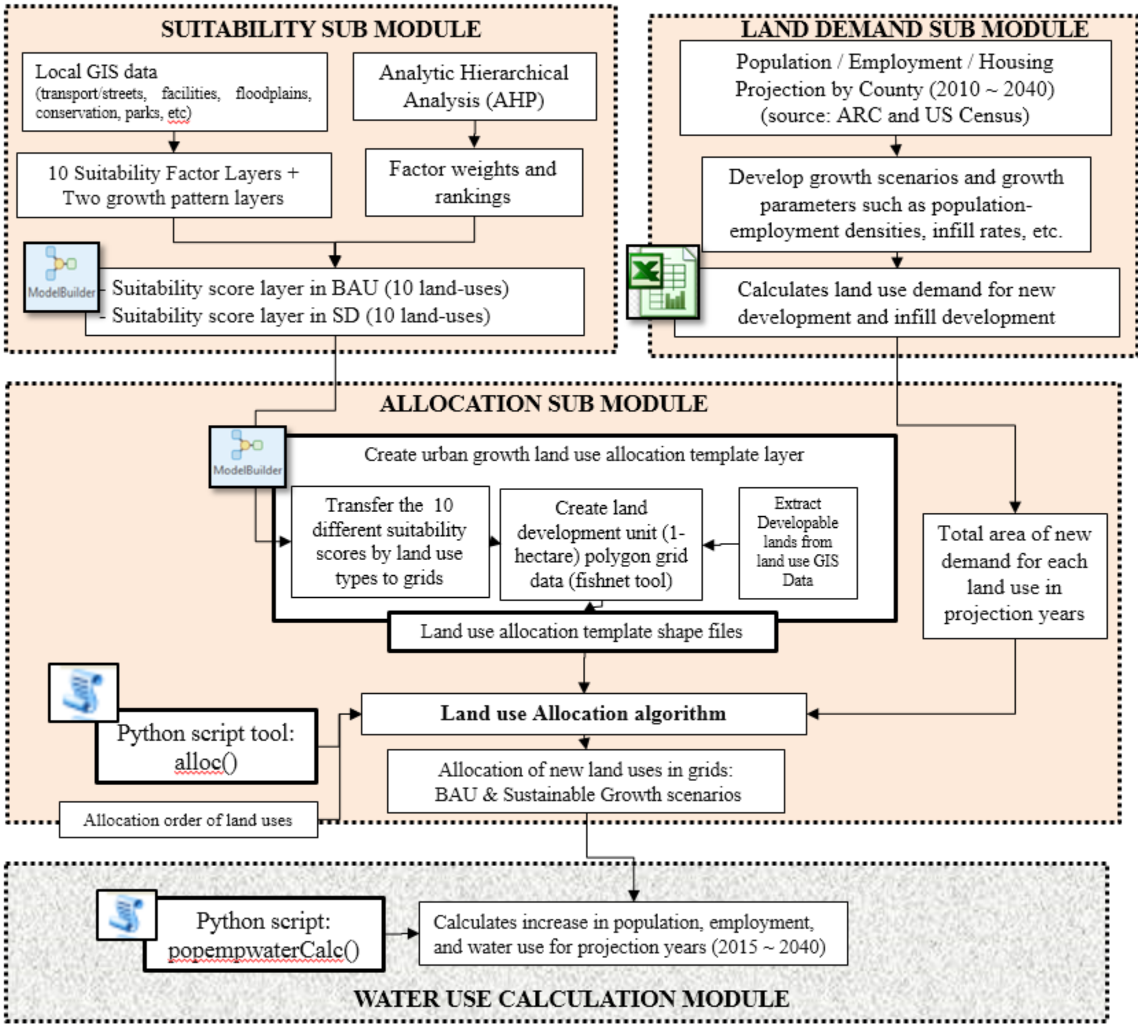


Figure 26: Modules in SWSPSS

Land Suitability module

Generating Suitability composite layers

The land suitability module contains a series of land suitability models built in ModelBuilder in ArcGIS environment. A Typical suitability analysis identifies ‘suitable’ land areas for future development by combining multiple GIS layers that represent local characteristics (Klostorman 2001, Malczewski 2004). These characteristics, often being collectively decided by planning experts, are put into the analysis as GIS factor layers, and converted into suitability scores to determine the prioritized developable lands.

Because multiple GIS layers are used as multiple criteria in determining the suitable locations through decision making process, this approach is typically called a multi-criteria decision making approach (MCMD) (Collins, Steiner et al. 2001, Malczewski 2006).

Fourteen GIS layers including two growth pattern layers and two masking layers are prepared using the GIS dataset published by Atlanta Regional Commissions (ARC, hereafter) to prioritize suitable locations for future land development. Each suitability factor layer contains the score from 10 (least suitable) to 90 (most suitable). Two growth pattern layers also have scores from 10 to 90 which represent likeliness to be developed in future depending on different spatial growth patterns, namely 'regional growth or activity centers oriented' and 'transit accessibility oriented'. Two masking layers, floodplain and conservations are used as Boolean layers to exclude non-developable region from future developable lands. The list of layers and GIS factor layers are shown in Appendix Section A (Figure 47 ~ Figure 53).

- Suitability factor layers: a layer of network distance to interstate highway ramps (S1) , a layer of distance from major roads (S2) , a layer of network distance to station and local town centers (S3), a layer of distance to rails (S4), a layer of city boundaries or sewer areas (S5), a layer of distance from lakes/rivers (S6), a layer of distance to parks (S7), a layer of distance to negative facilities (S8), , a layer of slope (S9), and a layer of existing industry (S10).
- Masking layers: 100 year flood plain (M1) and public land or conservation areas (M2)
- Growth Pattern layers:

- a network distance layer from regional growth centers defined by Atlanta regional commission (G1)
- a composite score layer (score 1 ~ 10) of proximity to existing transit system (MARTA stations, bus stops, and transit routes) (G2)

The suitability factors are integrated through map algebra techniques in order to generate final suitability score layer by each land use types. Map algebra or map overlay approach has been widely applied in land-use suitability (Malczewski 2004). Boolean overlay operation and weighted linear combination (WLC, hereafter) are considered the most straightforward and the most often employed methods in order to determine the composite map layer containing 'suitability scores or values' (Malczewski 2004, Drobne and Lisec 2009). In specific, WLC assigns weights of 'relative importance' to each attribute map layer in order to make the output composite layer store 'scaled suitability scores or scaled values', which can be understood as degree of likeliness to be suitable for the certain land use or conversion to be developed to other land use (Malczewski 2004). The calculation of suitability scores are represented as the equation below (Pereira and Duckstein 1993, Eastman 1999, Mendoza 2000).

Equation 4. Composite Suitability Score

$$\text{Composite suitability score} = \sum w_i X_i * \prod C_j$$

where:

w_i = weight assigned to factor I, X_i = criterion score of factor I, C_j = constraint j

Ranking and Weights: Analytical Hierarchy Analysis

In order to develop weights, this study has incorporated the Analytical Hierarchy Analysis (AHP, hereafter) method (Saaty 1990). The AHP can be employed to derive the weights for the alternatives when a large number of those alternatives involve or when aggregating the priority of all level of the hierarchy structure or alternatives are needed (Eastman, Jiang et al. 1998, Malczewski 2004). In order to decide relative importance among factor layers in composite score calculation, this study has created tables with 5-level ordinal scale (1: least important ~ 5: most important) to measure a pair-wise comparison distance among factor layers. (Table 39).

In Table 39, if two layers are in the same ordinal scale group, relative pair-wise comparison score of 1 will be given and put in the AHP matrix calculation. If individual layers in ordinal scale group become distant, the relative pair-wise comparison scores will be increased (or decreased) as shown in the AHP matrix by land use types. Because importance of factor layers play differently depending on land use types, 12 land use types are aggregated into four groups to distinguish a list of weights obtained from AHP matrix. Four groups are (1) single family residential, (2) multi-family residential, (3) construction-manufacturing-wholesales, and (4) TCU, retail, FIRE, service, and government or public institute. The AHP matrix tables are shown in the Appendix Table 47, 48, 49, and 50. As a result, the table of weights and rankings are determined as shown in the Table 51 and Table 52 in Appendix. The GIS overlay procedure adopts these tables to create composite suitability score layers.

Table 39: Degree of Importance for Suitability Factor Layers by Land Use Types and the Land Use Allocation Order

		Residential use		Employment use							
	Layers to Produce	Single family Residential	multi-family Residential	Construction	Manufacturing	Wholesales	TCU	Retail	FIRE	Services	Govern. Public
	Allocation Order	6	5	10	1	9	8	2	3	4	7
Increasing importance	Most important	Growth pattern layer (G1* or G2**)		S10_existing industrial use			Growth pattern layer (G1* or G2**)				
		S2_major roads	S3_station _town activity centers	S6_lakes_reservoirs			S3_station_town activity centers				
	More important	S5_city boundaries :sewer	S1_interstate Hwy exit ramps	S4_railroads			S1_interstate Hwy exit ramps				
		S1_interstate Hwy exit ramps	S2_major roads	s8_negative facilities			S5_city boundaries :sewer				
	Moderately important	S7_parks	S4_railroads	S5_city boundaries :sewer			S2_major roads				
AHP Importance		S6_lakes_reservoirs	S5_city boundaries :sewer	S2_major roads			S4_railroads				
		S3_station _town activity centers	s8_negative facilities	S1_interstate Hwy exit ramps			s8_negative facilities				
	Less important	s8_negative facilities	s10_existing industrial use	S7_parks			S6_lakes_reservoirs				
		s10_existing industrial use	S7_parks	Growth pattern layer (G1* or G2**)			S7_parks				
	Least important	S4_railroads	S6_lakes_reservoirs	S3_station_town activity centers			s10_existing industrial use				
degreasing importance		s9_slope	s9_slope	s9_slope			s9_slope				

Note: G1*= regional growth center oriented growth pattern layer for BAU scenario, G2**= transit oriented growth pattern layer for sustainable development scenario)

Construction for the ModelBuilder Models in ArcGIS

GIS suitability layers and suitability ranking/weights table are incorporated into GIS suitability model in ArcGIS ModelBuilder (Allen 2011). The model generates a series of raster dataset of suitability scores by different land use types. Because the model is designed to accept the weights of suitability layers as parameters, a user can modify the weights and compare results easily. (Figure 27 and Figure28). This study created a number of ModelBuilder models. (Figure 58 in Appendix A shows another example). The models are categorized into a number of toolset and stored in ArcToolbox in ArcGIS. Figure 29 shows the snapshot of the toolsets for SWSPSS.

Finally, suitability score layers of two scenarios by different land use types are generated. Suitability score layers by different land use type refer to the layer of single family (SF) residential, the layer of multi-family (MF) residential, the layer of Construction-Manufacturing-Wholesales use, and the layer of Retail- FIRE services-TCU-Government use (Figures 54 ~ Figure 57 in Appendix) are generated.

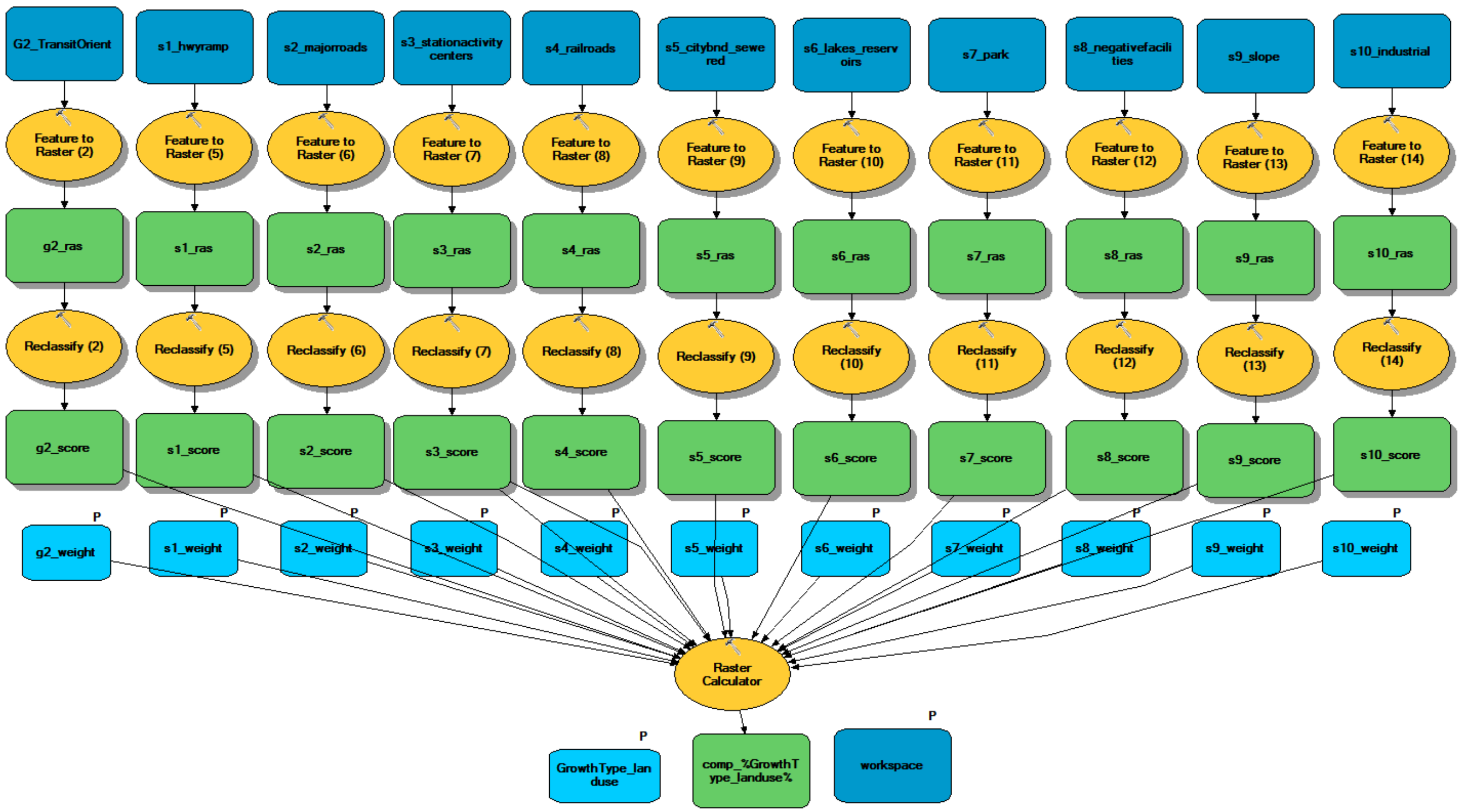
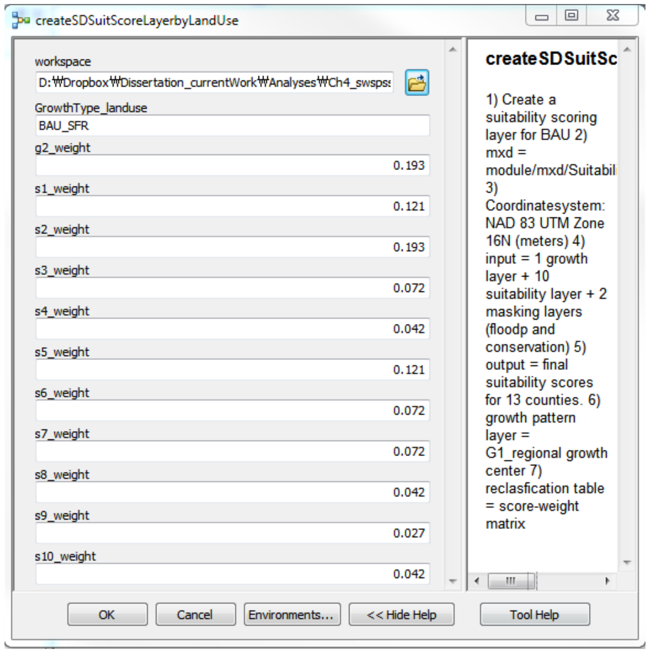


Figure 27. Example of ModelBuilder Model with Parameters



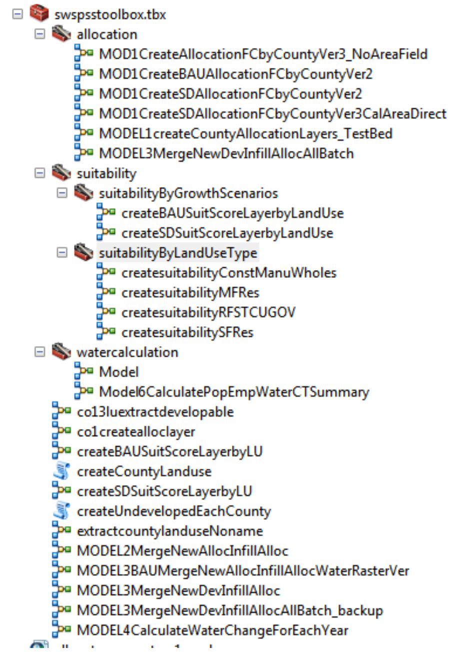


Figure 28: Example of Suitability Models and Weights Parameter (Left)

Figure 29. Example of Tool Sets and Models in SWSPSS (Right)

Once raster suitability score layers are generated, the results are transferred to a GIS layer containing 1-hectare size grids called ‘Land Development Unit Grid‘(LDUG, hereafter) layer. The LDUG layer, which is produced by applying ‘summary cell statistics’, ‘fishnet’ tool, and an ‘overlay’ geoprocessing tool’ in ArcGIS, stores the suitability scores corresponding to different land use development types. Figure 30 shows the graphical presentation of an LDUG layer for Gwinnett County.

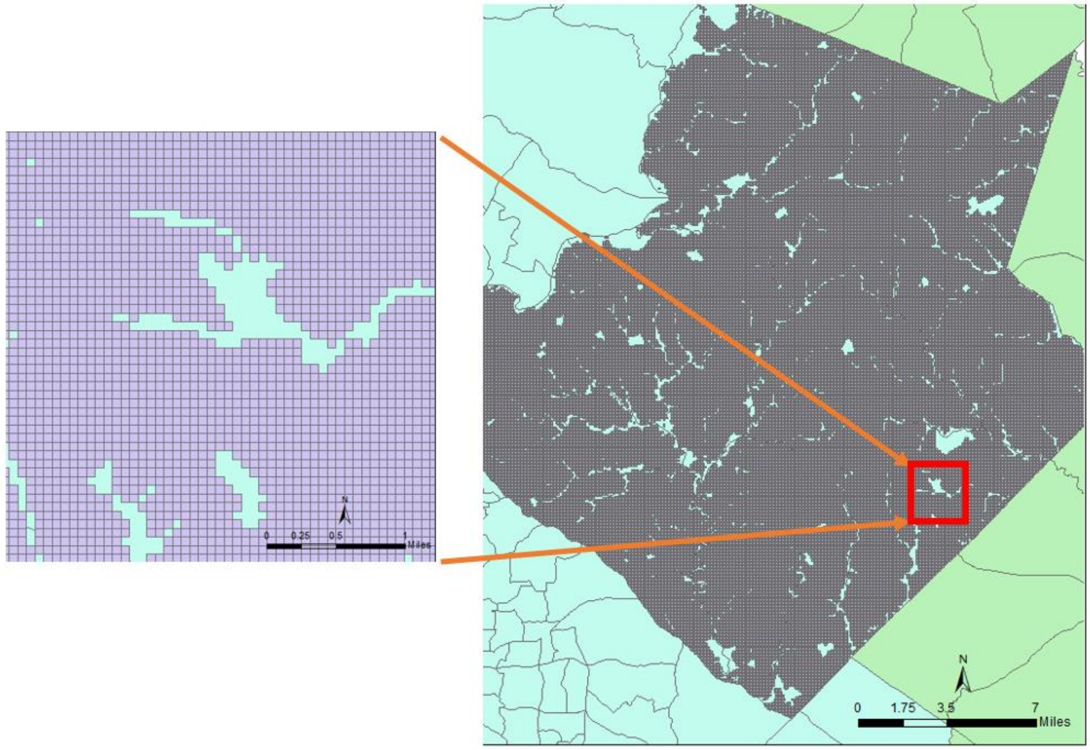


Figure 30: Creating a Land Development Unit Grid Layer (100 × 100 meters = 1 hectare)

The LDUG layer also contains information on land use type in base year 2010. Spatial information of 10 different land use classes **(s**ingle family residential, multi-family residential, wholesales, construction, manufacturing, TCU, industrial, FIRE-financial and real estate, and public-institutional use) are derived from LandPro 2009 dataset published by the Atlanta Regional Commission (ARC). A series of multiple models are constructed and executed to generate final LDUG layers for each county. The final LDUG layers becomes the allocation template layer in the allocation module in the SWSPSS later.

<u>Land demand analysis module</u>

The land demand module allows users to calculate the land demand in future projection years in the MS-Excel spreadsheet format (Figure 31). This interactive spreadsheet allows the user to modify the input parameters of average household size, percentage of single family housing, density of single family housing, density of multi-family housing, density of non-residential (employment) densities, and infill rates in future development. The range of parameters are decided based on Atlanta regional commission (ARC) projection data and reports. The population and employment projection information[4] at county level are obtained from ARC. The urban density changes in different growth scenarios until 2040 are incorporated into the land demand analysis as tabular data. Any user can modify the density values of single family housing, multifamily housing, and eight non-residential use densities in the land demand module. The range of parameters in densities are already discussed in Chapter 5.

The results of demand analysis show how much new land would be required in individual counties by different land use types under a hypothetical variation of density of population and employment. The results from this module are then transferred to the land use allocation module.

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4 http://www.atlantaregional.com/File%20Library/Info%20Center/Forecasts/ForWeb_-P40TU_PopHHEmp_TAZSDCounty.xlsx and http://www.atlantaregional.com/File%20Library/Info%20Center/Forecasts/ForWeb_-P40TU_EmpNAICSSIC_TAZSDCounty.xlsx

P11

	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1							SCENARIO:	BAU							
2		AVEHH_Size =	2.81	5 Core Counties Clayton, Cobb, DeKalb Fulton, Gwinnett	8 Non core conties		Density	5 Core Counties Clayton, Cobb, DeKalb Fulton, Gwinnett	8 Non core conties			NEW DEV Allocation %	Infill Allcation %		
3			SF_Den_POP=	21.075	14.05		SF_DEN_HH	7.5	5		BAU	0.8	0.2		
4			MF_Den_POP=	70.25	56.2		MF_DEN_HH	25	20						
5							Construction	70.9932665	70.9932665						
6							Manufacturi	40.624062	40.624062						
7							TCU	73.834974	73.834974						
8							Wholesale T	40.080431	40.080431						
9							Retail Trade	41.068851	41.068851						
10							FIRE	76.800234	76.800234						
11							Services	76.800234	76.800234						
12							Public Admi	76.800234	76.800234						
13															
14	ACRES	Hectares	PCT_SF10	PCT_MF10	VAC_Rate	INFILL_R10	INPUT_PCT_	INPUT_PCT_	INPUT_VAC_R	INPUT_INFIL_R	SD_PCT_SF	SD_PCT_MF	SD_VAC_R	SD_INFIL_R	Pop10
15	277,703.16	112,382.66	0.88	0.12	0.05	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	214,346
16	92,321.82	37,361.37	0.69	0.31	0.05	0.03	0.70	0.30	0.05	0.20	0.50	0.50	0.05	0.05	259,424
17	220,452.55	89,214.12	0.73	0.27	0.04	0.03	0.70	0.30	0.05	0.20	0.50	0.50	0.05	0.05	688,078
18	285,393.73	115,494.92	0.91	0.09	0.05	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	127,317
19	173,348.49	70,151.75	0.61	0.39	0.05	0.03	0.60	0.40	0.05	0.20	0.40	0.60	0.05	0.05	691,893
20	128,148.75	51,860.04	0.87	0.13	0.06	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	132,403
21	127,498.02	51,596.70	0.92	0.08	0.04	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	106,567
22	158,286.42	64,056.34	0.95	0.05	0.05	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	175,511
23	342,095.22	138,441.24	0.55	0.45	0.08	0.03	0.60	0.40	0.05	0.20	0.40	0.60	0.05	0.05	920,581
24	279,448.02	113,088.77	0.79	0.21	0.04	0.03	0.80	0.20	0.05	0.20	0.60	0.40	0.05	0.05	805,321
25	207,626.54	84,023.61	0.90	0.10	0.04	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	203,922
26	201,623.93	81,594.44	0.94	0.06	0.04	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	142,324
27	84,546.13	34,214.66	0.87	0.13	0.04	0.03	0.90	0.10	0.05	0.20	0.70	0.30	0.05	0.05	85,215

Figure 31: Example of Interactive Spreadsheets in Land Demand Analysis

<u>Land use allocation module and water calculation module</u>

The land use allocation module enables users to create GIS layers that can store the information of future land use, increase of population, increase of employees, increase of water use at 1-hectare size grids. In this module, the location of new developments are prioritized on the basis of suitability scores and new land use types are allocated to individual grids in the LDUG layer accordingly. The allocation algorithm is embedded as a function that updates old land use values in developable land grids to a new land use until total new land demands are met in every projection year. Figure 32 shows a graphical representation of the allocation algorithm. The function requires a pre-defined allocation order of land use types. This study case set the allocation order as following: ‘manufacturing’, ‘retail’, ‘financial/real estate(FIRE) service’, ‘multi-family residential’, ‘government’, ‘TCU’, ‘wholesales’, and ‘construction’. This study assumed that possible land use conversion to either new residential or employment uses would occur at first in existing ‘forest’, ‘agriculture’ and ‘other developable’ uses as ‘developable’ lands. . In every projection year, the algorithm finds the LDUG grid with the highest suitability score grid among three ‘developable’ land use type grids and updates it with a new land use value until a total size of new updated land reaches up to a given new land demand cap for corresponding use. For infill development, it is assumed that single family uses would be converted to other uses such as multi-family or non-residential use.

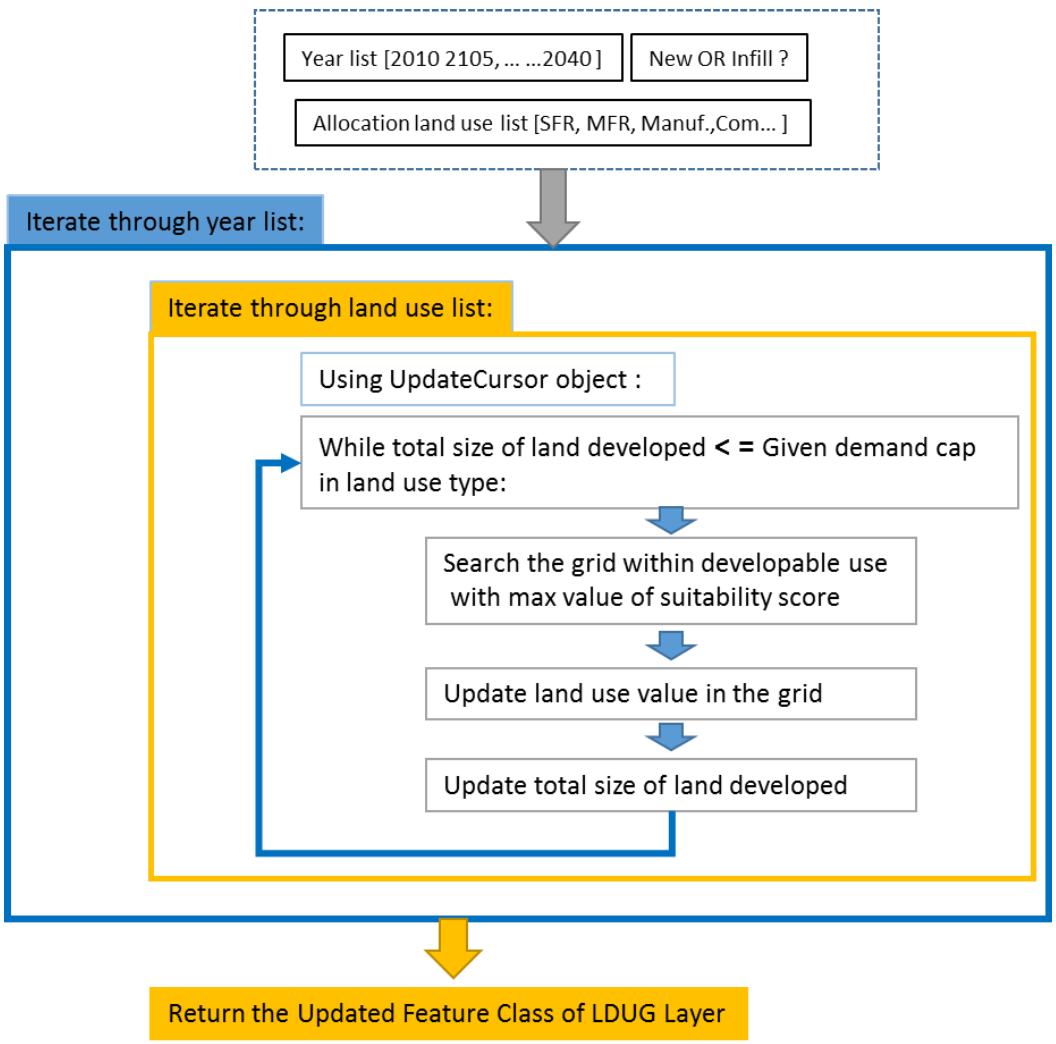


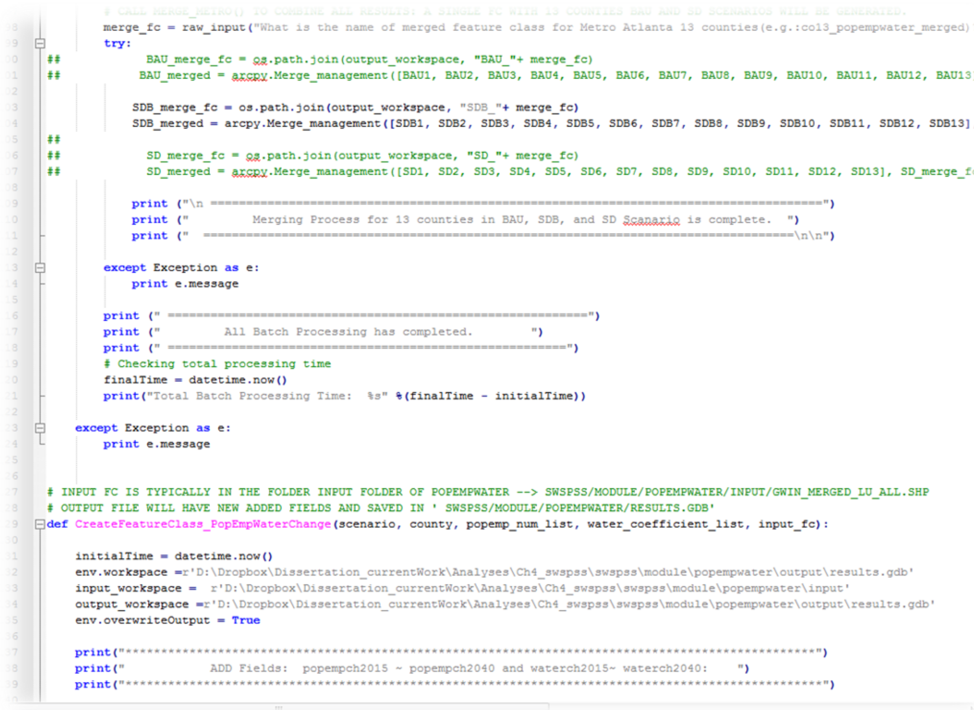
Figure 32. A Diagram of the Land Use Allocation Algorithm

The modules are designed to accept multiple input parameters: the county LDUG feature class, a list of population density by county, a list of employment density by county, a list of the order of land use allocation, and a list of county residential water use coefficients, and a list of employment water use coefficients. When the scripts are executed, the module returns a new county LDUG feature class. The new LDUG attribute table contains a list of fields of population change, employment change, and water use change by land use types from year 2010 to 2040. .

The modules including allocation algorithm are constructed as Python scripts as shown in Figure 33. In order to access geoprocessing tools and functions, an ArcPy module is imported in the scripts. Figure 34 presents the example of the allocation results after running the scripts in the allocation module.

Water use calculation module

Once individual LDUG layers by county are generated, the water use calculation script runs to calculate increase of population, employment and water use in each grid in LDUG layers by county for multiple projection years. Once the layers stores the information, they are exported as tabular dataset so that the system can calculate water use at census tract level. In order to aggregate the water use at census tract level, pivot tables are generated. Because the pivot tables contain the number of population or the number of employees in each census tract, a user can calculate a total water use in census tracts with conservation measures (ratios) are applied including RWH. The final output tabular data can be joined back to GIS spatial layers for further analysis. .



```python
    # CALL MERGE_METRO() TO COMBINE ALL RESULTS: A SINGLE FC WITH 13 COUNTIES BAU AND SD SCENARIOS WILL BE GENERATED.
    merge_fc = raw_input("What is the name of merged feature class for Metro Atlanta 13 counties(e.g.:co13_popempwater_merged)?
    try:
##          BAU_merge_fc = os.path.join(output_workspace, "BAU_"+ merge_fc)
##         BAU_merged = arcpy.Merge_management([BAU1, BAU2, BAU3, BAU4, BAU5, BAU6, BAU7, BAU8, BAU9, BAU10, BAU11, BAU12, BAU13]

        SDB_merge_fc = os.path.join(output_workspace, "SDB_"+ merge_fc)
        SDB_merged = arcpy.Merge_management([SDB1, SDB2, SDB3, SDB4, SDB5, SDB6, SDB7, SDB8, SDB9, SDB10, SDB11, SDB12, SDB13],
##
##          SD_merge_fc = os.path.join(output_workspace, "SD_"+ merge_fc)
##          SD_merged = arcpy.Merge_management([SD1, SD2, SD3, SD4, SD5, SD6, SD7, SD8, SD9, SD10, SD11, SD12, SD13], SD_merge_fc

        print ("\n ===============================================================================")
        print ("         Merging Process for 13 counties in BAU, SDB, and SD Scanario is complete.  ")
        print ("  ===============================================================================\n\n")

    except Exception as e:
        print e.message

    print (" ============================================================")
    print ("         All Batch Processing has completed.        ")
    print (" ==========================================================")
    # Checking total processing time
    finalTime = datetime.now()
    print("Total Batch Processing Time:  %s" %(finalTime - initialTime))

except Exception as e:
    print e.message


# INPUT FC IS TYPICALLY IN THE FOLDER INPUT FOLDER OF POPEMPWATER --> SWSPSS/MODULE/POPEMPWATER/INPUT/GWIN_MERGED_LU_ALL.SHP
# OUTPUT FILE WILL HAVE NEW ADDED FIELDS AND SAVED IN ' SWSPSS/MODULE/POPEMPWATER/RESULTS.GDB'
def CreateFeatureClass_PopEmpWaterChange(scenario, county, popemp_num_list, water_coefficient_list, input_fc):

    initialTime = datetime.now()
    env.workspace =r'D:\Dropbox\Dissertation_currentWork\Analyses\Ch4_swspss\swspss\module\popempwater\output\results.gdb'
    input_workspace =  r'D:\Dropbox\Dissertation_currentWork\Analyses\Ch4_swspss\swspss\module\popempwater\input'
    output_workspace =r'D:\Dropbox\Dissertation_currentWork\Analyses\Ch4_swspss\swspss\module\popempwater\output\results.gdb'
    env.overwriteOutput = True

    print("*******************************************************************************************")
    print("            ADD Fields:  popempch2015 ~ popempch2040 and waterch2015~ waterch2040:    ")
    print("*******************************************************************************************")
```

Figure 33. Example of Python Scripts in the Allocation Module.

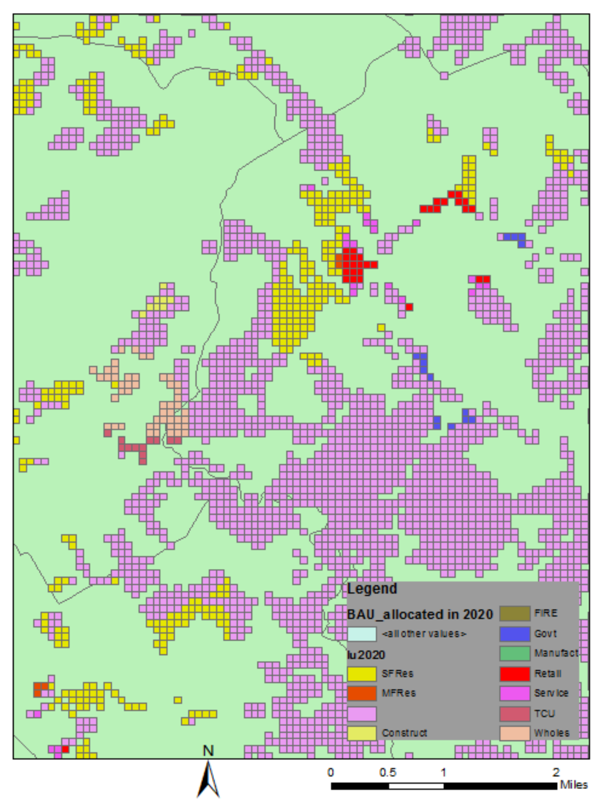


Figure 34. Example of Allocation Result (year 2020 -BAU scenario)

ESTIMATING VOLUME OF WATER FROM RAINWATER HARVESTING USING GIS BUILDING FOOTPRINT AND REGRESSION MODELS

The volume of RWH is calculated by measuring total roof areas. This study suggests a method to estimate the roofing areas in regression model. Once the regression model is developed, the total size of roofing areas are estimated for each projection year.

A similar approach to estimate area size of impervious surface including roofing area is attempted by Lee and French (2009). They employed a regression model to estimate the size of future impervious surface area using aerial photo imagery and regional impervious coefficients by land use type for metropolitan Atlanta (Lee and French 2009). This study uses actual building footprint GIS dataset, as illustrated in Figure 35, below.

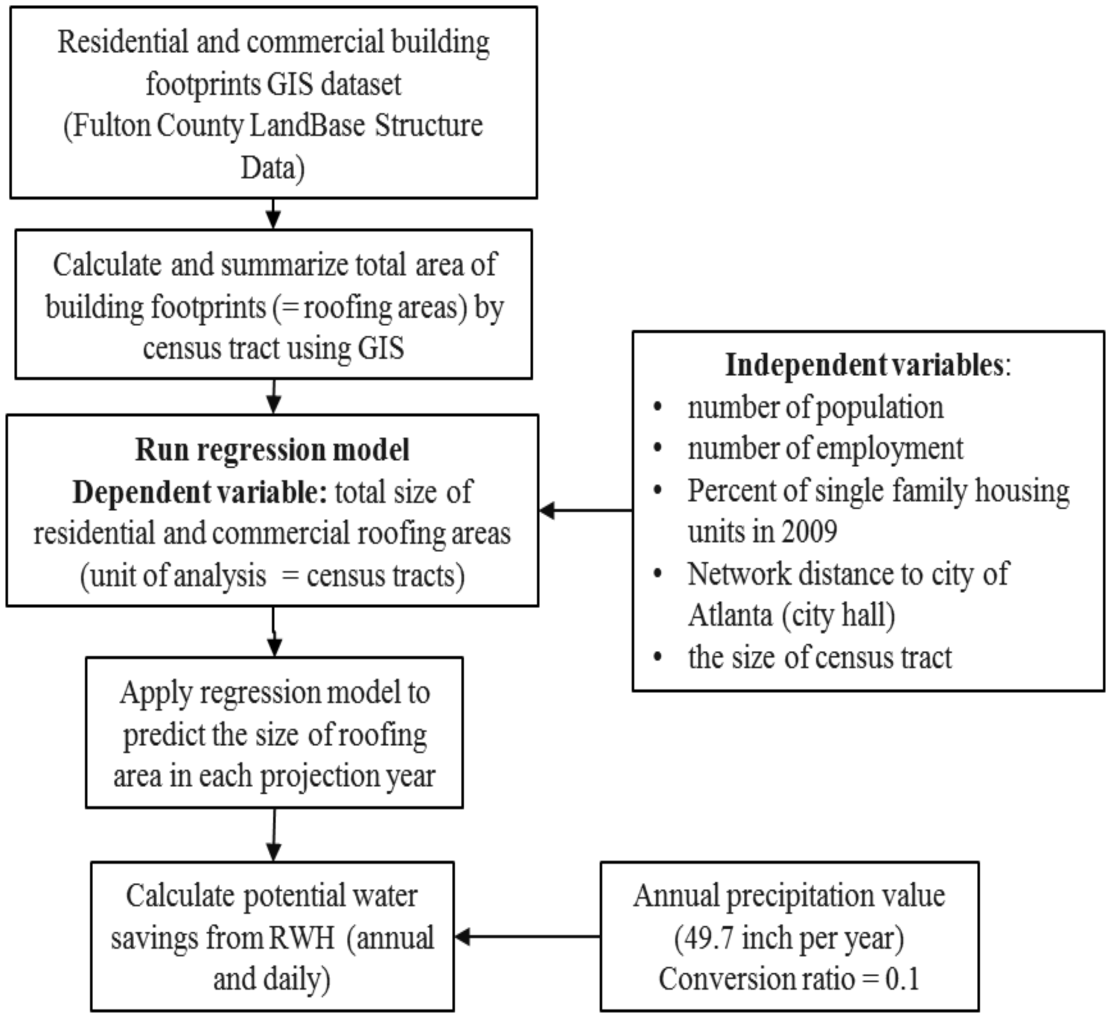


Figure 35: Analysis Steps to Estimate Water Saving Potential from RWH

The total size of roofing areas are derived from building structures GIS database called 'LandBase Structure Data' in Fulton County, GA. The database contains the spatial data of the base ground-level outline or footprint of buildings and other man-made structures in Fulton County (Figure 36). The unit of analysis is individual census tracts in the regression model. Total size of building footprint polygons were summarized by census tracts. Independent variables are total population, total employment, percent of single family housing units in 2009, network distance to city of Atlanta from tract centroid, and tract size in 2009. The size of tract is also included in the model as a control variable because larger sizes of tracts are more likely to have more residential and commercial buildings. A number of regression model types were tested with different form of variables (log-level models and log-log models) in case the variables show a high level of skewness.

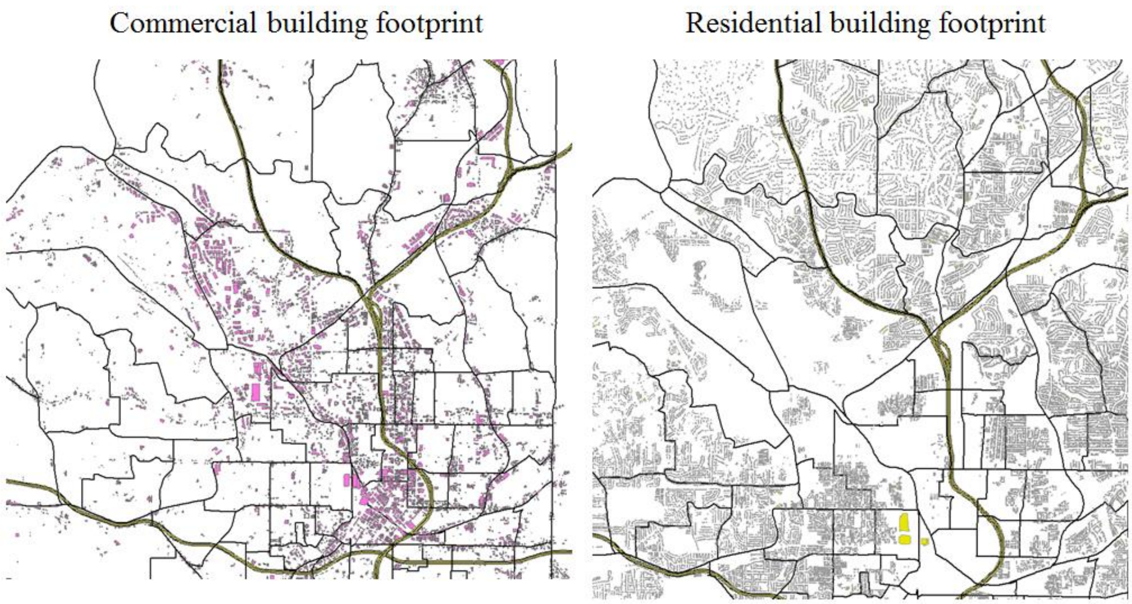


Figure 36: Residential and Commercial Building Footprints in LandBase, Fulton County, GA

Once the regression model is defined, the total size of roofing areas in each census tracts for every projection year is estimated. The roofing area for each projection year is estimated through regression models. Once the roofing area is calculated, the amount of potential rainwater harvesting from new development can easily calculated. This study assumed 10 percent as an efficacy ratio, representing a combination of a collection efficiency ratio and a coverage ratio. Collection efficiency refers to how much of water can be collected and stored in tanks through roofing areas, while coverage ratio is the percentage of total structures suitable for RWH device installation. In other words, the efficacy ratio represents how many individual residential or commercial buildings would be able to adopt the RWH devices and collect rainwater to offset the amount of water supply. Because limited availability regarding actual two ratios, this study only can hypothetically set the goal of RWH efficacy ratio as ten percent. As a result, 10 percent of roofing areas from existing buildings and 10 percent newly constructed roofing areas are accounted for RWH calculation.

The total size of roofing area in each census tract to RWH volume conversion is expressed as the first equation below (Equation 5-a). As a last step, estimated daily water demand with RWH are subtracted from the previously estimated water demand in 13 counties in the sustainable scenario at census tract level. The second equation (Equation 5-b) indicates that future demand through water supply systems will be reduced by increase of total size of the roofing area in each projection year.

Equation 5. Calculation of potential RWH water volume:

- *Equation 5-a: Daily water saving potential (gal)* = [49.7 inches (annual rainfall in ATL)[5] $\times$ area of roof surface (acre) $\times$43559 square feet/ acre $\times$ 144 square inches/square feet $\times$ 0.00433 gal/cubic inch] $\times$ 0.1 efficacy conversion ratio / 365 days
- *Equation 5-b: Total daily water in census Tract* i *in projection year t* = [total daily residential water use *i* + total daily employment water use *i*] - amount of daily RWH saving in year *i*

5 Source: NOAA, http://www.srh.noaa.gov/ffc/?n=rainfall_scorecard .

RESULTS AND DISCUSSIONS

RESULTS OF THE PROJECTION OF LAND USE CHANGE UNTIL 2040

SWSPSS has produced LDUG output GIS layers by county which contains newly allocated land use values, population numbers, and employment numbers stored in grids for each projection year. Figure 37 shows the different growth pattern result in terms of population and employment increase in graphics in two growth scenario, the BAU and the SD scenario. Table 40 is the summary result table of new land demand in 13 counties. Simulation results in both graphical representation and tabular format clearly show discernible differences between two scenarios: In the BAU scenario 151.7 thousand hectares of land (new: 121.4 thousand + infill: 30.3 thousand) is allocated to meet the development needs from 2010 to 2040, whereas SD scenario only needs 71.8 thousand hectares (new: 50.3 thousand + fill 21.5 thousand) during the same period. According to the results, low- and medium-density residential use is a dominant land use class future land use demand followed by commercial offices and commercial wholesale and construction use. These land uses cause substantial land conversion from forest and agricultural uses accordingly. In both cases, Gwinnett, Fulton, Forsyth, and Henry Counties are expected to experience significant conversion of undeveloped areas.

Once the allocation procedure up to 2040 is complete, another Python script in the allocation module ran, calculated and stored the number of population or the number of employees in grids in LDGU using a python dictionary data input which contains density values for land uses. Once iteration process completes, new development and infill areas (grids) stored the value of increased population or employee numbers. Figure 37 shows the example of 3D representation showing the pattern of newly increase of population and employment in 13 counties.

Table 40: New Allocation Land Demand in 13 Counties

	BAU		SD	
County	allocation in developable use (Ha)	allocation in infill (Ha)	allocation in developable use (Ha)	allocation in infill (Ha)
Cherokee	12,060	3,015	4,783	2,050
Clayton	2,849	712	1,230	527
Cobb	9,631	2,408	4,230	1,813
Coweta	6,918	1,729	2,724	1,167
DeKalb	7,559	1,890	3,359	1,439
Douglas	5,033	1,258	2,020	866
Fayette	2,547	637	1,081	463
Forsyth	15,393	3,848	6,049	2,592
Fulton	16,290	4,073	7,351	3,150
Gwinnett	20,276	5,069	8,447	3,620
Henry	12,497	3,124	4,917	2,107
Paulding	7,413	1,853	2,899	1,242
Rockdale	3,000	750	1,197	513
Total	121,467	30,367	50,286	21,551

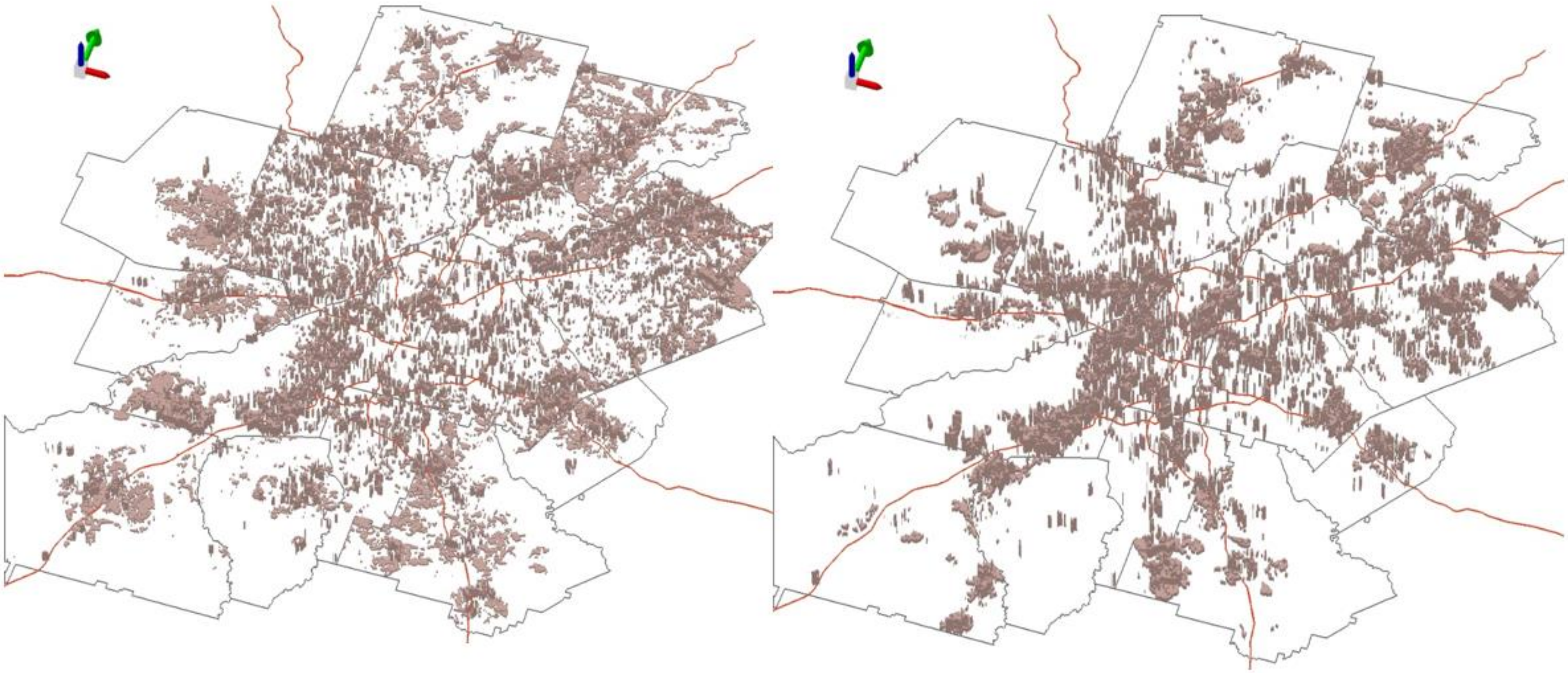


Figure 37: Increase of Population or Employment from 2010 to 2040 in Two Growth Scenarios, the Business-as-Usual (BAU) and the SD Scenarios

Note: 1 ha grid polygons are extruded for 3D visualization;
Extrusion height = increase of population or employment * 25 (meters)

WATER USE PROJECTION IN THE BAU AND THE SD BEFORE RWH IMPLEMENTATION

The system also calculated water use based on both the BAU and the SD scenario accordingly. Figure 38 presents the result of projected spatial pattern of urban water demand. As shown here, this graphic visualization allows us to observe spatial patterns of future water intensity. Such information can be imperative in identifying high priority areas for additional water-sewer infrastructure systems. This is one of many benefits that integration of land use change modeling in PSS and impact analysis of conservation policy implementation.

Figure 39 and Figure 40 show that water demand in 13 counties would be changed from 585 million gallons per day in 2010 to 997.5 million gallons per day by 2040 unless current water use profile and growth pattern were to change; however, the SD scenario will achieve 154 million gallons per day savings, a 15.5 percent reduction from the BAU scenario. The source table of charts are available in Appendix B section (Table 54 and Table 55). According to the analysis results, without any conservation effort and continuance of current urban growth pattern accompanied with population and employment trends (i.e., the BAU scenario), the water demand of the 13-county study area would increase from 585.8 million gallons per day in 2010 to 997.5 million gallons per day by 2040 due to rising population and employment. However, under conditions that encourage sustainable water use, the total water demand in the same study area would be reduced to 843 million gallons per day without rainwater harvesting (RWH) option by 2040, which is equivalent to 15.5 percent (154.2 million gallons of water saving) less than the BAU scenario.

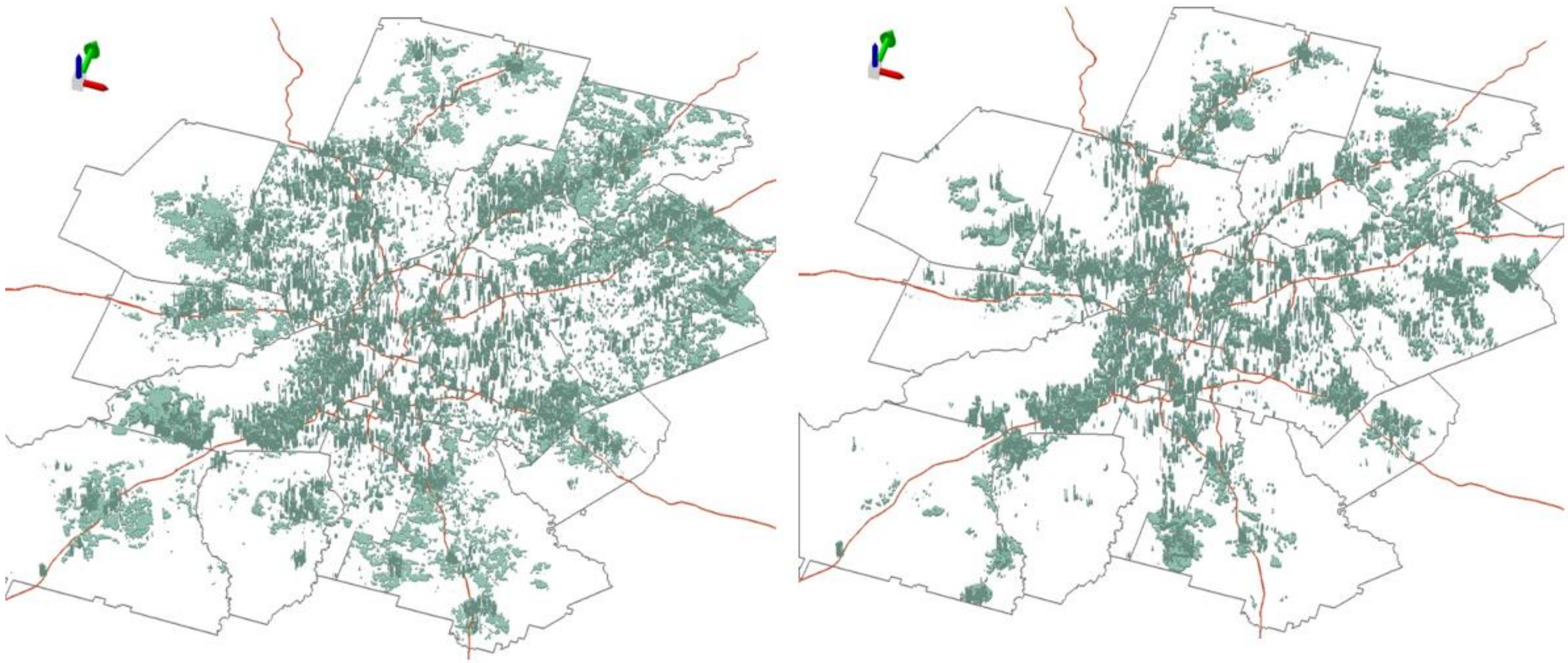


Figure 38. Projected Spatial Pattern of Urban Water Demand in the BAU and the SD

Note: 1 ha grid polygons are extruded for 3D visualization;
Extrusion height = Gallons per day / 0.5 (meters)

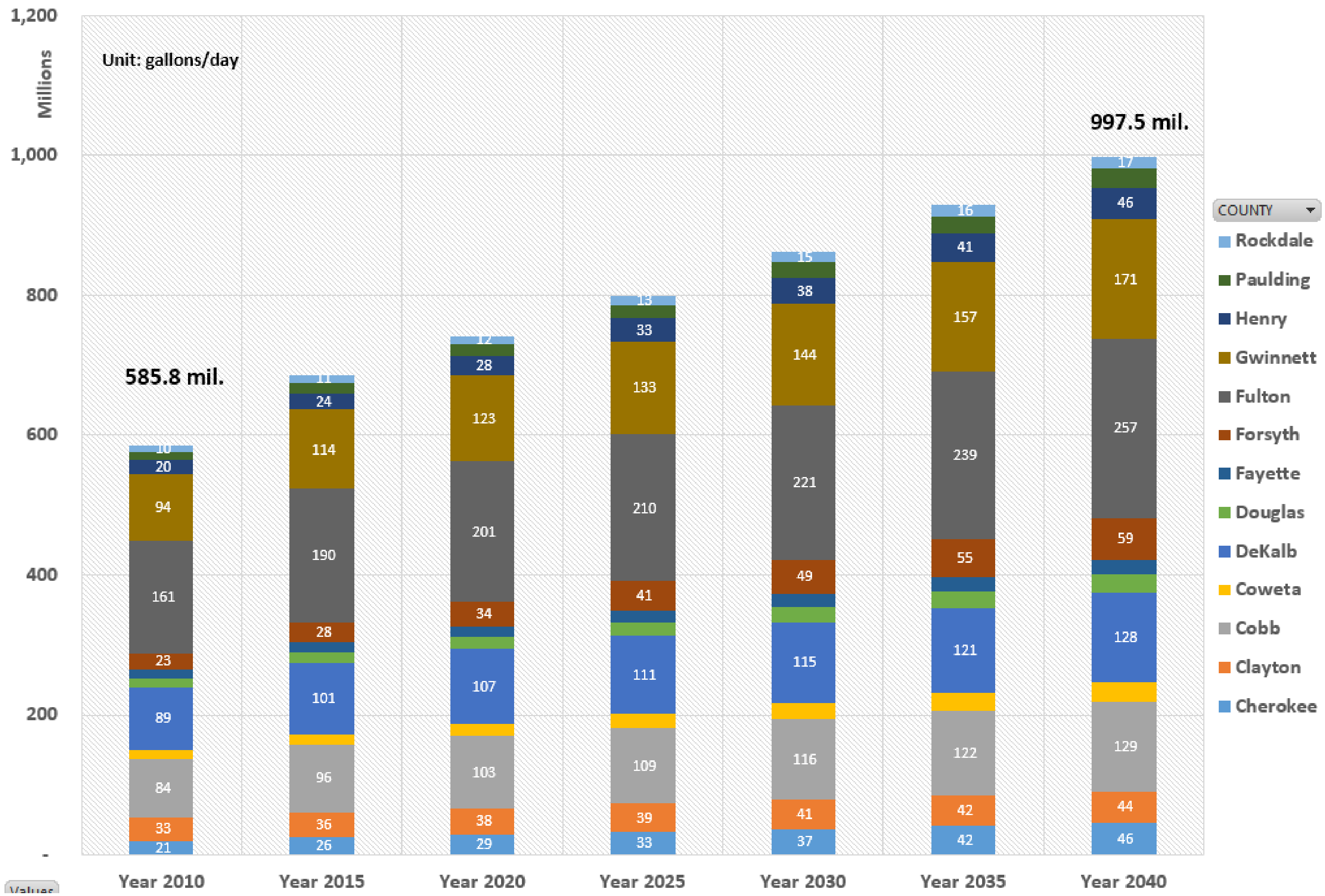


Figure 39: Results of Projected Water Use in the BAU

(See Table 53 in Appendix B)

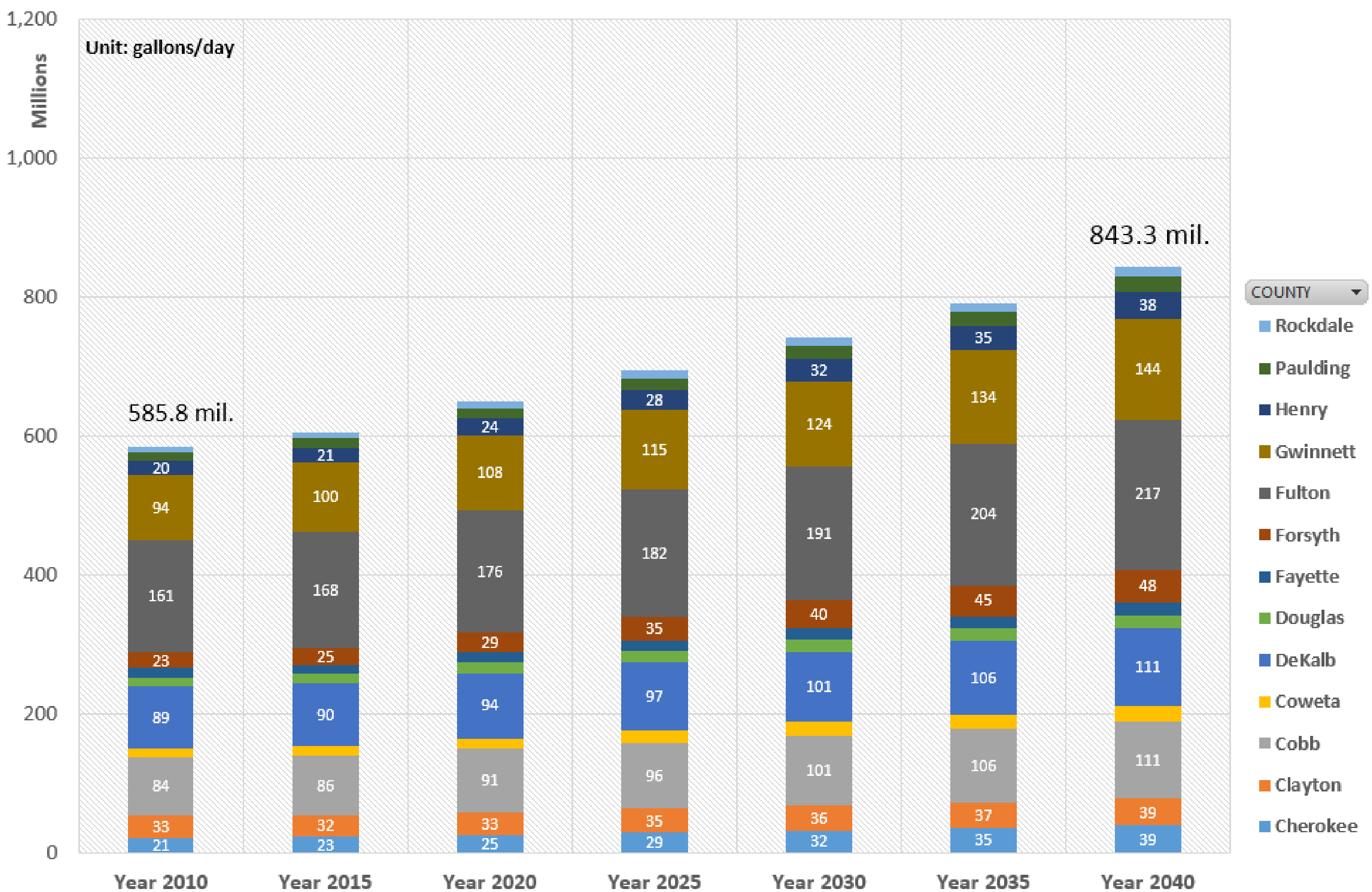


Figure 40: Results of Projected Water Use in the SD

(See Table 54 in Appendix B)

WATER USE PROJECTION FOR THE SD WITH RWH IMPLEMENTATION

<u>Results in regression model to estimate roofing area and water saving calculation</u>

The regression modeling analysis for rainwater harvesting potential was run and the results are described as below. First, Table 41 presents the summary of descriptive statistics from the regression analysis.

Table 41: Descriptive Statistics and the Bounds of Variables for the Regression Model: RWH Analysis

Variables	OBS.	Min.	Max.	Mean	Std. Dev.
Size Roofing (SQ.FT.)	165	181,584	36,428,169	5,724,047	5,741,287
POP2009 (person)	165	281	35,201	5,35.9	4,349.7
Emp2009 (person)	165	.0	47,750	4,114	7,109
Percent of single family HU (1 = 100%)	165	.027	1.0	.540	.276
Network distance to Atlanta city hall (mile)	165	.12	29.4	8.43	7.33
Tract size (Acre)	165	22.1	45,757.5	2,048.4	4,510.5

According to the results, population, employment, percent of single family housing, network distance from census tract centroid to Atlanta city hall, and size of tract were significant independent variables that explained 91 percent of the variation (Adjusted R-square) in the total size of residential and commercial roof area. (Table 42).

Table 42: Regression Model and Variables Statistics for Rainwater Harvesting Potential

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig.	Durbin-Watson
1	.956[a]	.914	**.912***	.247	**.000***	**1.988**

a. Predictors: (Constant), log of size of Tract in ACRES, log of total employment , Network Distance to City of Atlanta City Hall in mile, population , percentage of single family housing units

b. **Dependent Variable: Log of total area of all structure in SQ.FT. (excluding unknown uses) F = 339.7**

Table 43: Regression Model and Variables Statistics

Dependent Variable: LN_Total_Area_Roofing_SQ.FT.				
Independent Variables	Unstandardized Coefficients	Standardized Coefficients	t-statistics	Significance p>|t|
	B	Beta		
Constant	10.549		58.861	.000***
Population	4.105E-005	.215	5.855	.000***
LN_EMP	.171	.324	11.086	.000***
Percent of SFH	.375	.125	4.187	.000***
Network Distance to City hall	-.012	-.110	-2.746	.007***
LN_Size of census tract in acres	.454	.649	13.655	.000***

where: LN_total_area_roofing_SQ.FT.: Logarithm of roofing area (square feet)

POP: number of population (person) L_EMP: Logarithm of employment (person)

Percent of SFH: percent of single family housing unit in census tract

Network Distance to City hall: Network distance in mile to Atlanta city hall from census tract centroid

LN_Size of census tract in acres: Logarithm of Census tract area (acres)

The t-statistic of independent variables and the F-statistic test also show the overall model is statistically significant (Table 43). Since the variables included log-transformations, the R-square value is not directly interpreted as the prediction power and taking exponentials to retransform the function might produce a bias (Stynes, Peterson et al. 1986); however, the transformed model would still provide better results than raw-data model.

Not surprisingly, population and employment, percent of single family housing unit coefficients in the model showed a (+) sign, which indicates a positive correlation between the independent variables and a total size of roof surfaces in census tract. Interestingly, the coefficient of the percent of single family housing has a positive sign, which means that the total size of roofing areas in the low-density single-family-oriented development areas may become greater than denser-multi-family oriented areas if other conditions are equal. This makes sense because a typical suburban single family residential house has more roof per capita than urban multi-family housing. This supports a policy option to offset a higher volume of water consumption in suburban area. Based on the result, the total size of roofing areas in each tract was predicted using the regression equation below:

Equation 6. Calculation for roofing area size from the regression model:

Log (square feet of roofing area in Tract $_{i,\ k}$) =

[10.549+ 0.00004105* (population $_{i,\ k}$) + 0.171* log (employment $_{i,k}$) + 0.375* percent of single family housing $_{i,k}$ - 0.012 * distance to Atlanta city hall $_{i}$ + 0.454 * log (size of tract in acre $_{i}$)]

Where: i = census tract, k = projection year.

The total size of roofing area by census tracts are converted into potential volume of RWH based on the equations stated in method section. After applying the equation above, Figure 41, 42 and Table 44 show the estimated roofing area (SQ.FT.) in each projection year, the change of roofing are between 2010 and 2040, and predicted rainwater harvesting potential in gallons from 2010 to 2040. The result shows that 194.5 thousand acres of new roofing areas would be available until 2040, which is equivalent to 72 million gallons per day potential water savings through RWH collection scenario[6].

[6] There were a couple of RWH gallon per day potential value estimates that exceed actual total water use in census tracts as outliers. In order to calculate water use within a reasonable range, the expected estimates from outliers are replaced with the mean RWH potential values in each corresponding year. The census tracts where mean RWH values are used are; (1) 13117130600 (Census FIPS) (S Forsyth) for year 2025, 2030, 2035, and 2040; (2) 13135050202 (North Gwinnett) and 13223120600 (East Paulding) in year 2040 and (3) 13077170500 (SW Coweta) in year 2030, 2035, 2040. The values replaced

Table 44: Potential Savings from Rainwater Harvesting: Regression Model and Prediction of RWH

Year	2010	2015	2020	2025	2030	2035	2040	Change 2010-2040
Predicted roofing Area (Acres)	117,933	121,467	128,582	139,494	152,815	170,839	194,551	76,617
Total rainwater harvesting potential (Mil. gallons/day)	43.61	44.92	47.55	51.58	56.51	63.18	71.9	28.33

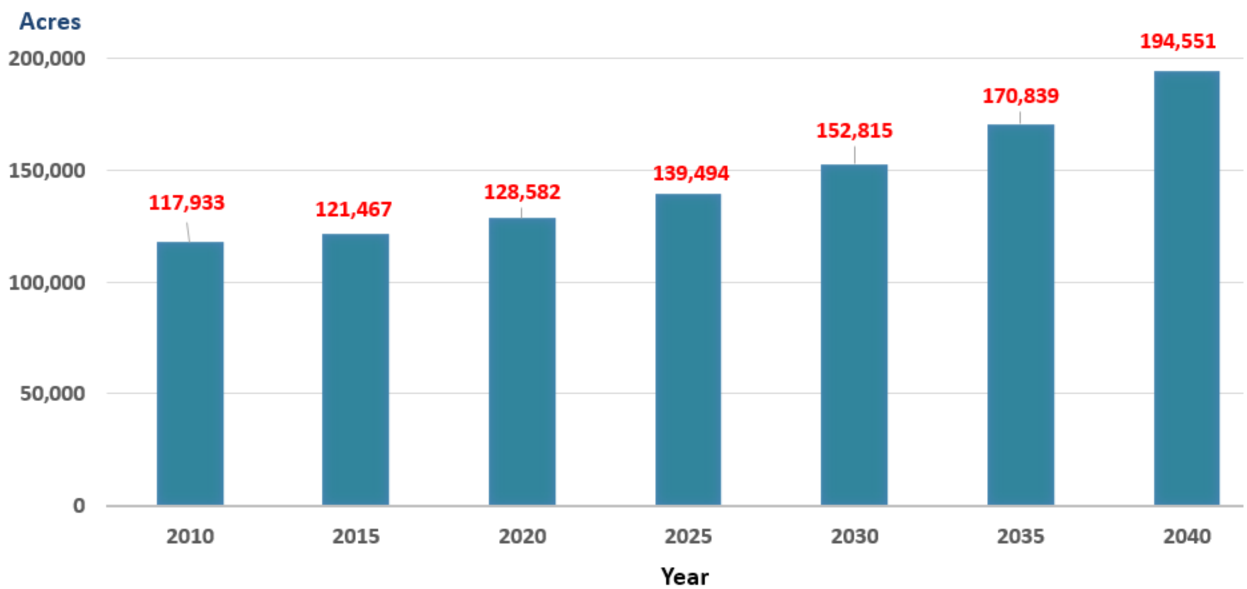


Figure 41: Predicted total size of roofing area

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with are: Year 2025 = 250,732 gal/day (or 14,766,106 sq.ft.), Year 2030 = 343,144 gal/day (or 20,208,407 sq.ft.). Year 2035 = 527,384 gal/day (or 31,058,688sq.ft.) Year 2040 = 695,548 gal/day (or 40,962,178 sq.ft.)

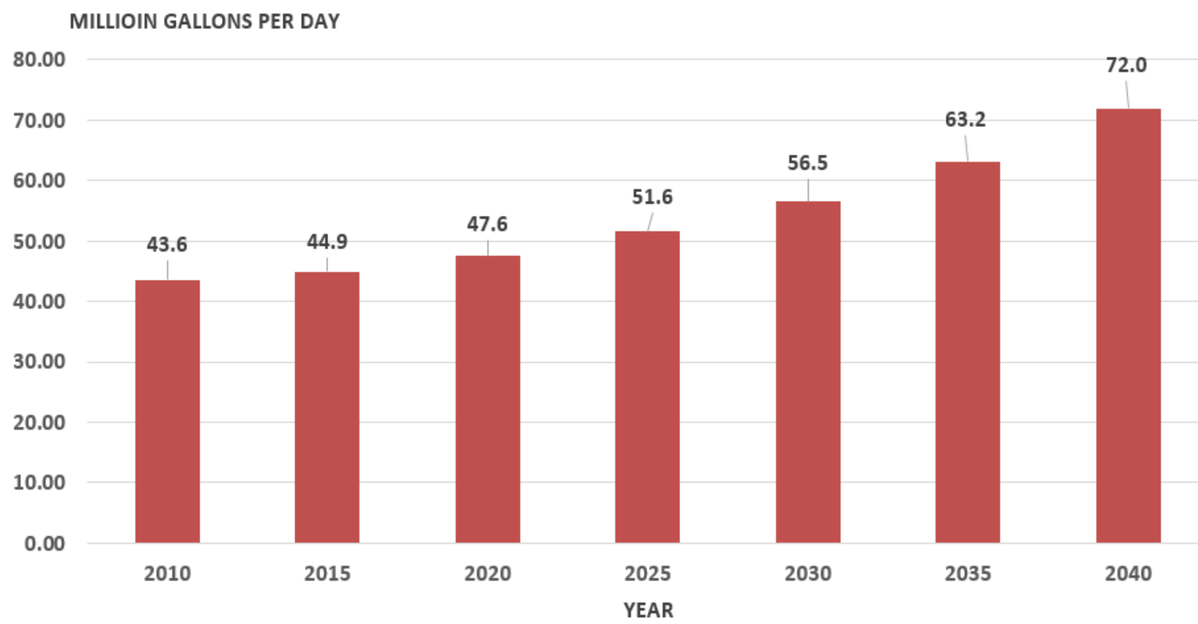


Figure 42: Predicted Rainwater Harvesting Potential (million gallons per day)

The RWH conservation option analysis result suggests that additional water saving of 72 million gallons per day from new building roofing area by 2040 can be achieved, the equivalent of 7.6 percent additional savings from the BAU scenario.

The RWH strategy is particularly suited to Atlanta because of the metropolitan area's humid climate. However, the magnitude of volume of water savings estimated here is calculated based on a series of assumptions and hypothetical scenarios; significant shifts in climate patterns, for example, could mean actual rainfall levels differ greatly than projected here. Therefore, the actual volume of savings would needs further verification. Actual implementation of a sustained RWH strategy would also require political commitment and consensus building, which are not accounted for in the SWSPSS.

Scenario C (SD + RWH implementation) is the combination of the SD scenario outlined earlier and the water savings from RWH estimated here. The newly estimated water demand in

Scenario C for each projection year is calculated by subtracting RWH water saving from the projected water demand in the sustainable scenario at census tract level. Figure 43 represents the result of Scenario C. The source table of Scenario C is available in Appendix section (Table 58).

Table 45 presents a final summary table of projected water demand in the BAU and the SD, both with and without the RWH conservation option. As shown in the table, the SD with RWH requires a total 771.4 million gallons of water per day in 2040. This is an additional reduction of 7 percent from the BAU scenario.

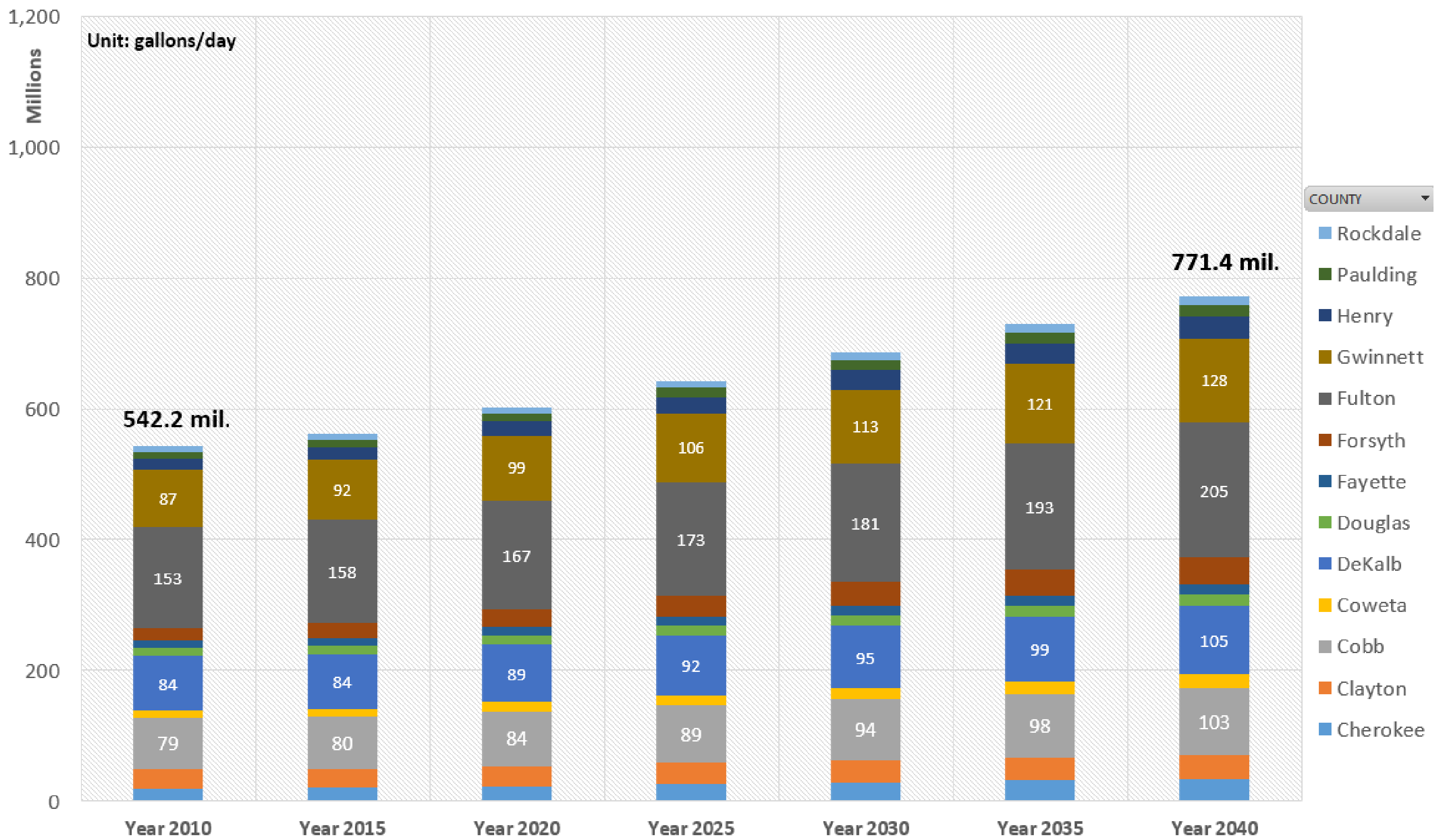


Figure 43. Results of Projected Water Use in the SD with RWH Implementation

(See Table 55 in Appendix B)

Table 45: Estimated Water Demand in BAU, SD and with/without RWH (unit: gallons per day)

Scenarios	Type\ Year	2010	2015	2020	2025	2030	2035	2040
Scenario A (BAU)	Residential	384,272,290	418,717,354	446,730,293	480,230,881	516,269,004	555,497,383	597,958,576
	Employment	201,552,965	267,317,698	295,382,269	319,190,461	344,976,687	373,245,913	399,600,510
	Total	585,825,255	686,035,052	742,112,561	799,421,341	861,245,691	928,743,296	997,559,087
Scenario B (SD: compact growth and efficiency improvement)	Residential	384,272,290	371,483,456	392,533,470	417,937,522	444,963,619	472,995,887	503,763,780
	Employment	201,552,965	234,719,722	257,428,207	276,408,811	296,985,764	319,002,737	339,589,557
	Total	585,825,255	606,203,178	649,961,677	694,346,333	741,949,383	791,998,624	843,353,337
Scenario C (SD and RWH)	Total	542,209,982	561,281,056	602,408,275	642,757,254	685,433,747	728,817,303	771,402,749

ADVANTAGES OF USING SWSPSS FOR SUSTANAINABLE FUTURE

This chapter illustrated how integrating land use into water demand forecasting could be done in a GIS modeling framework. The GIS modeling framework in SWSPSS is designed to connect two separate areas of research, land use and water resource planning. The analysis results for the metropolitan Atlanta case study show that a sustainable water use scenario combining two different approaches, one that focuses on increasing density and one that concentrates on reducing water use through technological means, can be effectively incorporated into the GIS modeling framework.

This study found that using SWSPSS offers several distinctive advantages to planners as a part of planning practice. They are: (1) scenario testing to find sustainable policy alternatives in collaborative environment; (2) improved customization ability; (3) mapping capability for local and regional water management discussions.

First, one of many advantages that planners can enjoy when using PSS is scenario testing in a collaborative environment with a map-centered approach (Pettit 2005). Planners can change and calibrate sustainable water-use scenarios to test out possible alternatives by adjusting various input parameters such as a list of ‘weightings of importance” in the suitability module, residential and employment density by county in the demand module, and county GPCDs and GEDs in the water use calculation module. This testing process for numerous alternative scenarios can occur in a collaborative environment where local and expert knowledge are shared. This helps planners to find the most effective sustainable scenario through calibration at some extent (Pettit, 2005) while working with people in other disciplines.

Second, these simple and easily modifiable models can be developed in ArcGIS software environment. The results for the metropolitan Atlanta case study suggests that adopting individual representative daily per-capita water use coefficients for different land uses in simple models can successfully provide a reasonable long-term water use demand range. Because SWSPSS is built in the ArcGIS (ESRI) environment as a collection of ModelBuilder models and Python scripts, users have almost full control in customizing the GIS model framework, and in setting the scenario settings, the input and output data, and the modeling parameters, including densities and water use profile. In general, most commercial stand-alone PSS prohibit users from replacing underlying assumptions, parameters, and equations (Pettit, 2006). Unlike stand-alone hardwired PSS, the GIS models embedded in SWSPSS can be customized, updated, and utilized for other types of natural resources demand projection. Developing models and tools in ArcGIS using ModelBuilder and Python scripts offers a modeling framework that is more flexible and transparent.

Third, the mapping component of the SWSPSS increases its utility and the communicability of its results. In the metropolitan Atlanta case study, SWSPSS was able to not only quantify future water demand but also to produce maps regarding spatial patterns of water use. For example, Figure 44 presents the results of hot spot analysis (Mitchell 1999) derived from new water use increase until 2040 in the BAU scenario and the SD. Hot spot analysis uses vectors to identify the locations of statistically significant "hot spots" and "cold spots" in data in terms of high and low values. Hot stop analysis results can answer the question of where high/low values for a particular attribute cluster spatially. The two maps of hot spot analysis results present high and low volume of expected water demand by location.

Planners can conduct such analyses to engage in sustainable water use planning practice. In case of hot spot analysis, planners can see which community or local areas (in this case, hot spots) can be expected to produce rapid increases in water demand and whether those areas are spatially clustered or not. Because hot spot analysis includes the degree of clustering, local planning authorities can identify the areas which may require new provision of new infrastructure or increased maintenance.

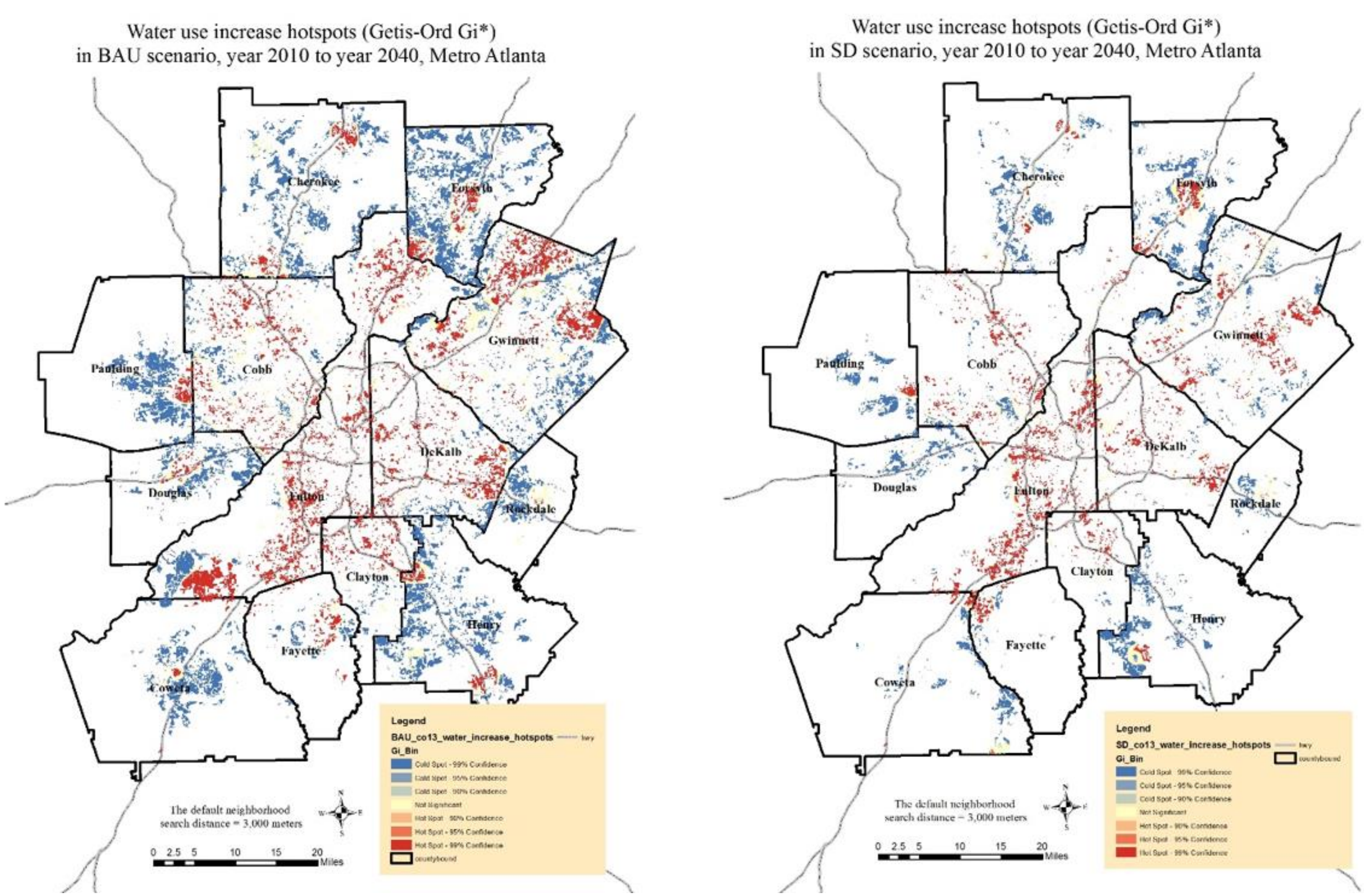


Figure 44. Hot Spot Analysis from water demand increase in 2040 (Left: BAU, Right: SD)

Figure 45 and Figure 46 present another example that enrich the sustainability discussion in metropolitan case study context. The maps show the volume of water increase until 2040 with a dot density map style: one dot represents 250,000 gallons per day. The maps show clear distinction between two scenarios (BAU and SD) in terms of the volume of water changes and locations of such changes. By comparing the results shown in the maps, this study found that BAU would cause more substantial withdrawals from two surface water sources than SD in future. As mentioned in Chapter 1, the region extract about 87 percent of water supply from the Lake Lanier (top right in figures) and Lake Allatoona reservoirs (s left in figures), which are considered to be a sole source (MNGWPD, 2009; Missimer et al, 2014). Because these reservoirs are subjected to severe supply limitations caused by droughts, BAU would threaten the viability of the water sources and supply reliability in the region in the long run.

Adding the water basin GIS layer to the maps also provides interesting insights in terms of waste water management planning and interbasin transfer (IBT). An interbasin transfer takes place when water is withdrawn from one river basin, and distributed for use in another river basin, with no water returning to the basin of origin. IBTs are common in metropolitan Atlanta, but controversial for some counties which straddle two or more river basins and water-waste water systems. Currently, IBT is a key element in supplying water throughout the Metro North Georgia Water District (MNGWPD 2009). The majority of water interbasin transfer is from the Chattahoochee River Basin (Table 46).

Table 46. Summary of Interbasin Transfers in Metropolitan North Georgia Water District (MNGWPD 2009)

Net Interbasin Transfers		
Source Basin	Receiving Basin	Net Transfer (million gallons per day)
Chattahoochee	Ocmulgee	100
Chattahoochee	Oconee	7
Coosa	Chattahoochee	14
Flint	Chattahoochee	2
Flint	Ocmulgee	5

For example, Cobb County in Metropolitan Atlanta withdraws water from both the Etowah and Chattahoochee rivers, then discharges a majority of the waste water to the Chattahoochee, resulting in a net loss of water from the Etowah River. DeKalb and Gwinnett Counties withdraw water from the Chattahoochee River Basin and discharge to both inside and outside of the Chattahoochee Basin (MNGWPD 2009). Geographic data of future water use pattern generated in SWSPSS provides approximate projection for net water changes by IBTs. When comparing two maps for BAU and SD, BAU is likely causes greater net transfer among basins than SD because new demand increase is much higher and dispersed in space, although further investigation would be needed to quantify the amount of IBT and correlation with development. Monitoring the possible net gain and loss impact of IBTs within basins in future is imperative, given the repeated legal and political, in addition to environmental, issues surrounding water use.

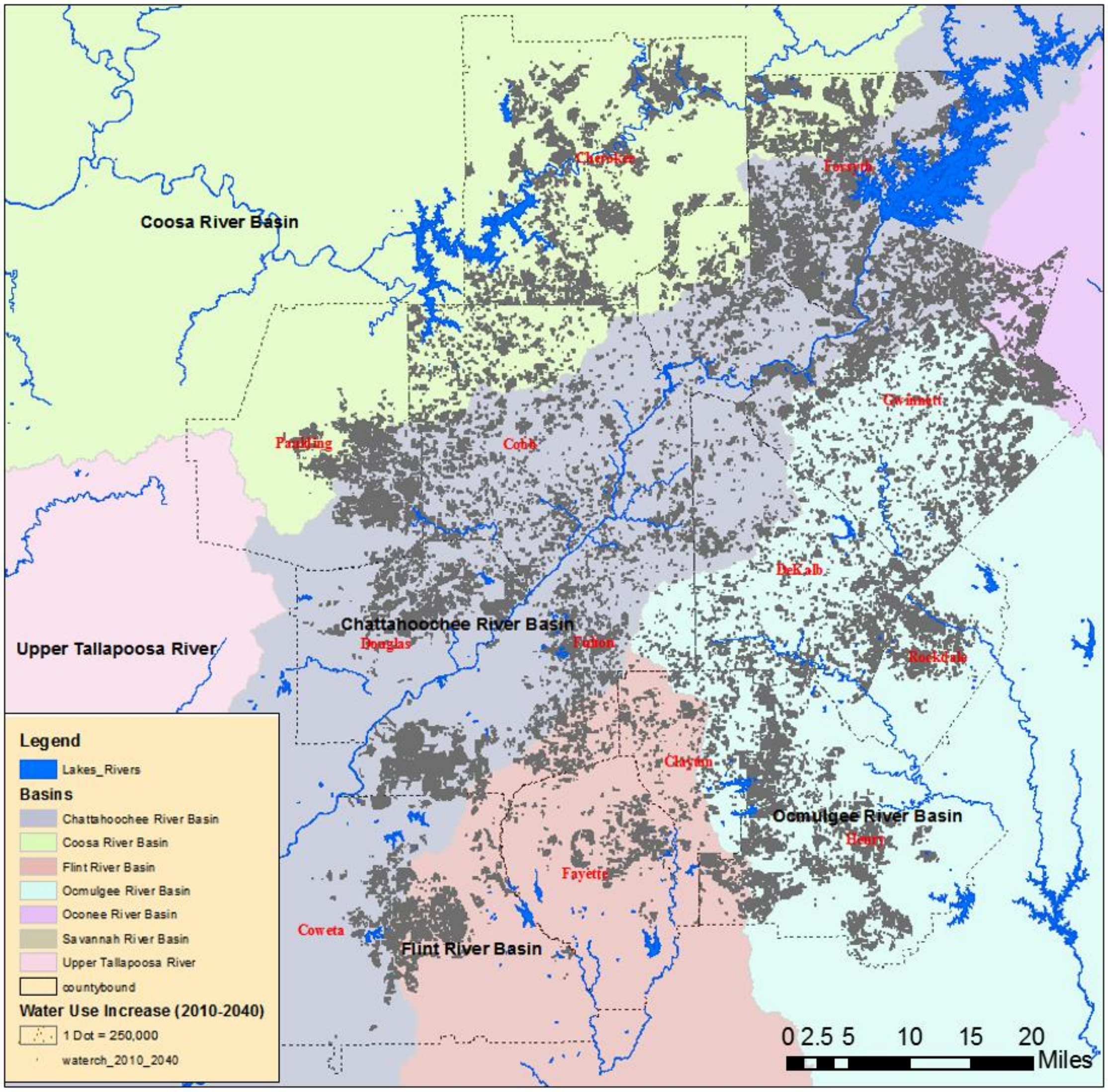


Figure 45. Net increase projection in metropolitan Atlanta until 2040: BAU

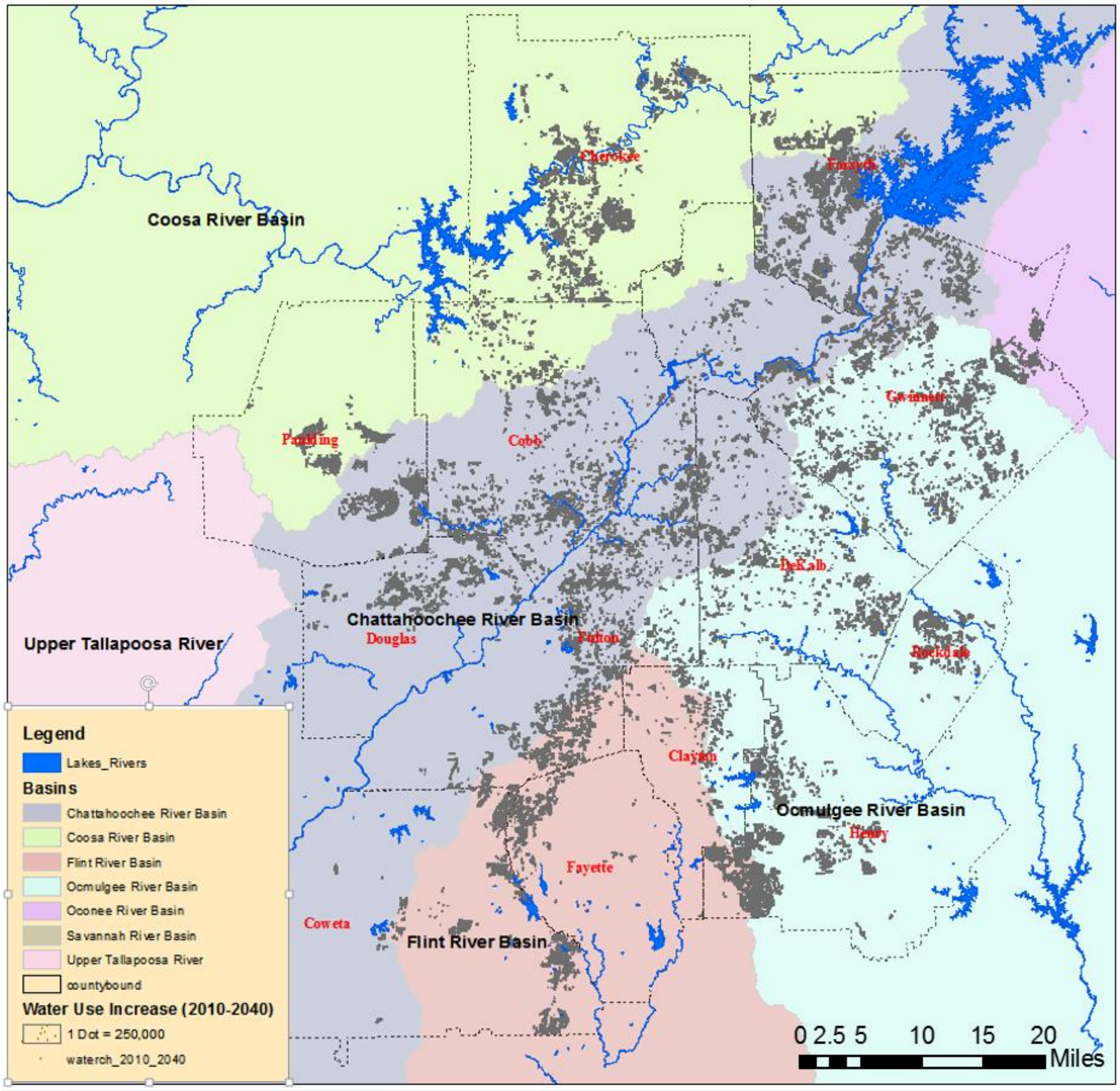


Figure 46. Net increase projection in metropolitan Atlanta until 2040: SD

LIMITATION OF CURRENT VERSION OF SWSPSS AND FUTURE IMPROVEMENT

Several limitations in the analysis framework of the SWSPSS and the research design should be acknowledged. . First, SWSPSS is designed to project long-term water demand at large scale geographic areas; therefore, SWSPSS is not suitable for predicting short term water use changes, nor it is appropriate for water use estimation at individual water consumer level. Second, the GIS land use models integrated in SWSPSS is static and deterministic in nature because the analysis requires a pre-defined set of assumptions and parameters, exogenous socio-economic data input that are not changed during the analysis procedure. . Third, SWSPSS adopts representative daily per capita water use rates (GPCD) for different land uses and end use characteristics. This indicates that the volume of water use calculated in each unit of analysis, 1-hectare polygon grids in a LUDG layer, represents merely a total water use volume aggregated by water consumption for different water use groups in terms of land use types. Therefore 'the general principle of composition and noise' can be applied, which is the theory that overall totals can be obtained by adding all the disaggregated groups together, as forecasting errors will tend to "net out" to zero if enough large customers (samples) are combined (Billings and Jones 2008).

Fourth, due to the lack of water device inventory data and conservation measures information, sustainable water use and development scenario (SD) has to assume GPCD or GED values associated with end use sectors would be reduced reasonably by a certain hypothetical percentage value(s). Collecting more accurate water device data in residential and non-residential uses is extremely challenging. Even if such data were available, the effectiveness of conservation measures and water consumers' behaviors which affect magnitude of water savings would be still unclear; therefore, possible water reduction ranges has to be determined by multiplication of representative water use rates, GPCDs and GEDs, while using a hypothetical reduction ratio, approximately 20 percent in most categories of GPCDs and GEDs. The parameters entered into the SWSPSS would have to change depending on more accurate data on water-use behavior.

Finally, overall design of SWSPSS is similar to 'What if?' (Klosterman 1999), in that both are rule-based models. Typically, rule-based models assume that various assumptions associated with suitability, future trends in urban developments and effectiveness of public policies are correct. Hence SWSPSS, like other rule-based models, is limited by its built-in assumptions. Unless these assumptions prove to be correct, the magnitude of actual water savings by actual conservation policy could be either underestimated or overestimated. Therefore, without concreate verification methods to test the assumptions about conservation measures and urban growth modeling parameters, such as residential densities and percentage of single family housing, actual numbers of water demand and savings reported here should be interpreted with caution.

Improving functionality of SWSPSS framework in future study

Based on limitation of current research design, a couple of suggestions can be made to improve SWSPSS framework. First, it is strongly recommended to switch the unit of analysis from 1-hectare size grid to actual parcels in GIS data. Parcel data contain more specific information such as the location of water consumers, physical characteristics of buildings, and current land-use types. As discussed in the earlier section on parcel-level analysis, incorporating a parcel database would allow users to estimate water trends at a geographically smaller scale such as the community neighborhood level. Presumably, geographic locations for analysis can be easily scaled up once this parcel-based inventory and GIS database are incorporated into SWSPSS, which would allow greater quality and accuracy in local water demand forecasting.

Second, incorporating high-resolution digital-imagery data into SWSPSS would open up another research opportunity for sustainable water use management planning. Because a GIS parcel database contains geo-information of individual lots, it is possible to estimate outdoor water use more accurately by extracting geo-information such as existence of outdoor pools, the size of building rooftops, the size of lawns or turf grass from satellite imagery and digital photo-geometric imagery data. As discussed earlier, spatially explicit variables such as location of water consumers, lot size, and existence of outdoor pools are important predictors in estimating volume of water consumption at the household level. Measuring actual rooftop sizes for individual buildings will improve the accuracy level of the RWH estimation method discussed in this chapter. Combining multiple GIS data and digital imagery data would provide more information for policy control variables discussed in both the parcel-level analysis and the RWH estimates.

Third, the user interface of SWSPSS also needs improvement so that users can use the system without difficulty. It is important that models and tools in PSS should be well organized and easily comprehensible. The user interface of the PSS should be intuitive so that any users can easily follow each step of the analysis. Specific potential improvements include: (1) adopting the graphic user interface (GUI) of Tkinter in Python language; (2) creating a toolset that would contain all ModelBuilder models, Python script tools; and (3) adopting Add-on menu functionality available in ArcGIS environment.

CHAPTER 7

SUMMARY AND CONCLUSIONS

This study explored the challenges of transitioning to more sustainable water use in urban areas in the U.S., with a case study of metropolitan Atlanta. This study examined interdisciplinary literature and developed empirical analyses to demonstrate the utility of considering both land-use patterns and technological advances in sustainable water planning. This concluding chapter summarizes findings, discusses implications for sustainable planning and policy intervention as well as future research, and concludes with a discussion of a planner's role in sustainable water management practices.

SUMMARY OF RESEARCH

To investigate sustainable urban water use and planning practice suggestions, this study conducted both theoretical and empirical analyses. In the theoretical discussions, this study reviewed several topics: sustainable water use and urban metabolism; long-range forecasting methods for urban water use; water conservation, including rainwater harvesting; the drivers of urban water use; and urban water use projections in existing planning support systems. The theoretical discussions revealed that not many studies have discussed how integrated land use-water models could be used to promote sustainability in urban water use management. This study has thus proposed a sustainable water use framework containing two approaches combined, the 'land use development configuration approach' and the 'technological solution approach'. The 'land use approach' is closely related to development configuration, built environment, and urban growth policies, whereas the 'technological solution approach' refers mostly to water device efficiency improvements and water reclaiming strategies, such as rainwater harvesting (RWH).

Beyond theoretical discussion, this study has conducted three inter-related analyses with different geographic scopes; (1) a county-level analysis of 1,501 counties in the United States; (2) a parcel-level analysis of three cities in Fulton County, Georgia; and (3) the development and testing the SWSPSS on thirteen counties in metropolitan Atlanta.

To return to the initial research questions:

(1) What are the relationships between urban form/urban development and urban water use?

(2) What are the implications of incorporating land-use variables into water-use planning?

(3) How can planners formulate sustainable urban water use projections by adding knowledge about local water use and land development patterns?

(4) How can planners benefit from an integrated water-land use model to promote local and regional water sustainability?

(5) Which approach is more effective in creating more sustainable water use: a land use-development (urban form) approach or a technological solutions (including rain water harvesting) approach?

To answer the first and the second questions, this study collected county water withdrawal data in the U.S. in 2005 and data in a series of variables of interest for 1,590 counties. The results from the cross-sectional statistical analyses suggested that urban development configuration variables, as policy control variables, such as county population density and percentage of single family detached, are positively correlated with the county urban water use in gallons per capita per day (GPCD); however, this study also acknowledges that the magnitude of the relationship is small. Other independent background variables, income, temperature, inside metropolitan statistics area, excessive water use for thermoelectric power are also positively correlated with county GPCD.

Next, parcel-level analysis was conducted using actual water billing data in 2006 in north Fulton County, Georgia, to examine whether the annual volume of water use is correlated with properties of single family residential, especially lot size. This study utilized a spatial error model (SEM) to capture unobserved effects, including spatial-autocorrelation. The results confirmed that lot size as a policy control variable is positively correlated with the volume of annual water use; however, it should be acknowledged that the expected water reductions by decreasing lot size is modest in magnitude. Other background variables—assessed property values as proxy of household income, number of floors and age of building structure—are also positively correlated with water volume.

Regarding the third question, this study reviewed interdisciplinary literature that suggested ranges of per capita water use rates by different user groups associated with land use types. Three different scenarios, business as usual (BAU), sustainable development (SD) and SD with rainwater harvesting (RWH), were proposed, to be incorporated into a GIS modeling framework.

The forth research question is related to the development of the integrated land use-water model to project urban use in ArcGIS environment using ModelBuilder and Python scripts. This study employed the conceptual framework from ‘What-if?’ (Klosterman, 1999) and produced models and script tools to generate spatial data of long-term water demand. The GIS-based modeling framework is called ‘Sustainable Water use Scenario-based Planning Support System’ (SWSPSS). This study illustrated how this land use-water model can be used for the case study for metropolitan Atlanta.

In order to predict potential savings through rainwater harvesting, building footprint GIS data for Fulton County, Georgia was collected and calculated total size of roofing areas by census tracts. A log-level type simple OLS regression model was developed to predict total size of roofing areas by census tracts. The results were incorporated to the SD to examine the range of additional savings. Finally, the study results proposed that SD would allow 13 counties in metropolitan Atlanta to reduce total projected volume of water used by 114 million gallons per day in 2040. Rainwater harvesting has a potential to reduce that number by a further 72 million gallons per day.

This study also found that using SWSPSS offers distinctive advantages to planners: (1) scenario testing to find sustainable policy alternatives in collaborative environment; (2) increased opportunities to customize the analysis; (3) mapping capability for local and regional water management discussions.

POLICY IMPLICATIONS

Policy implications and the answers for the last research question were discussed through interpretation of coefficients from two regression analyses in Chapter 3 and 4.

First, if a county's population density increased by 10 percent, the county GPCD for the total water use and urban water use are expected to decrease by 3.9 percent and 1.76 percent respectively. Similarly, a 10 percent decrease of single family housing (SFH) detached share in county would result in -4.8 percent change in the urban water use GPCD.

Second, in the parcel-level analysis, when lot size is reduced by 0.1 acres and 0.2 acres (mean = 0.4 acres), about 0.95 percent and 1.89 percent reduction, respectively, in annual water use (mean = 105,733 gallons) could be expected.

However, this study found that such land use changes would not necessarily function as a better alternative to technological solutions when seeking long-term water conservation. Specifically, an increase in population density by 10 percent, a decrease in percentage of SFH by 5 percent, and a reduction in average lot size by 0.1 acre would reduce GPCDs by 2.2 gallons, 3.0 gallons, and 1.14 gallons, respectively. On the other hand, technological solutions approach in literature suggest approximately a maximum of 10.3 gallons or 24 gallons savings, which are substantially higher (See Table 3).

Whether controlling urban form (i.e, increasing density and percent of multi-family housing) to reduce county GPCD is the most effective planning strategies or not is debatable; however, urban form-development configuration approach should still be considered. Because metropolitan Atlanta is currently expected to add 2.3 million additional population in the next 30 years, even a small degree of changes in daily per capita rates could converted into substantial water savings.

Therefore, when local and regional water planning authorities devise sustainable water management plans, the land use change component should not be a lesser priority than other conservation regulatory initiatives and approaches. Sustainable water use planning in practice should combine the land use-development (urban form) approach and technological solutions approach together to lead community to a more sustainable path, as illustrated in Figure 4 in the introductory Chapter 1.

PLANNER'S ROLE IN SUSTAINABLE URBAN WATER USE PLANNING

This study has found that planners have great potential to contribute to sustainable water planning.

First, planners are familiar with local and regional demographic characteristics, the built environment, natural resource conditions, and socio-economic history and variability, all of which can inform and improve water resource management and water demand forecasting.

Second, planners influence zoning regulations and community-urban-regional growth policies in mid- and long-range planning. Since controlling urban form-land use configuration can influence the changes in daily per capita water use rates, planners offer new potential to water-management authorities and other parties interested in water conservation and sustainability.

Third, planners can form the scenarios and keep the assumptions as realistic as possible. As Klosterman (2012) pointed out, planners can promote more open and democratic policy making by making ‘explicit and factual assumptions’ and simple ‘exploratory’ models. By developing simple GIS-scenario based integrated land use-water models, planners can provide informative spatial data and maps for collaborative processes, where expert knowledge and openly democratic discussions can take place for more sustainable water planning.

FUTURE TYPES OF RESEARCH

This dissertation study suggests several promising avenues for future research.

First, a future study can attempt to conduct county-level analysis with the water withdrawal data for more than one period to explore changes over time. In this case, panel data analysis and time-series analysis would increase the understanding of the correlation between land use and water use.

Second, for parcel-level analysis, a future study could explore the relationship between seasonal water use and other variables of interest, including lot size. Because most outdoor water use is consumed in spring and summer, investigating correlations between lot size and seasonal water use only will provide more meaningful insights to reduce outdoor water use by controlling residential density and associated zoning policies. Using data such as actual lawn area and existence of outdoor pools, taken from satellite imagery, would refine our understanding of seasonal changes of water use in urbanized areas further.

Third, adopting satellite imagery data and aerial photo-geometry data would offer the opportunity to extract actual building roofing areas. This will improve the analysis in RWH discussed in Chapter 6.

Fourth, the user interface of SWPSS needs improvement so that users can access the system conveniently even without any expert knowledge. A couple of methods are recommended for further study: (1) adopting various modules available in Python language including the graphic user interface (GUI) of Tkinter; (2) creating toolsets that would contain all ModelBuilder models, including Python script tools; (3) adopting add-on menu functionality available in ArcGIS environment. These attempts can greatly improve the SWSPSS's functionality and utility to a wider variety of planners and interested conservationists.

CONCLUDING REMARKS

This study makes a unique contribution by connecting two separate areas of research: land use and water resource planning. Future research should continue this exploration of the relationship between urban form and urban water use patterns. This study confirmed correlations between land use-compact urban form variables and urban water use. Local and regional water management authorities and utility providers should continuously promote conservation policies. Even though a strictly land-use-based approach to water conservation would be less effective than a technologically dependent approach, recognition of the urban form and land use changes are essential in sustainable water planning.

To envision sustainable urban communities, planners should have keen understanding of spatial variability of urban settlement patterns and should be able to quantify such impacts on water demand. This study will enrich the discussion as to why conservation and proper growth policies are critical in local and regional water demand planning.

APPENDIX A

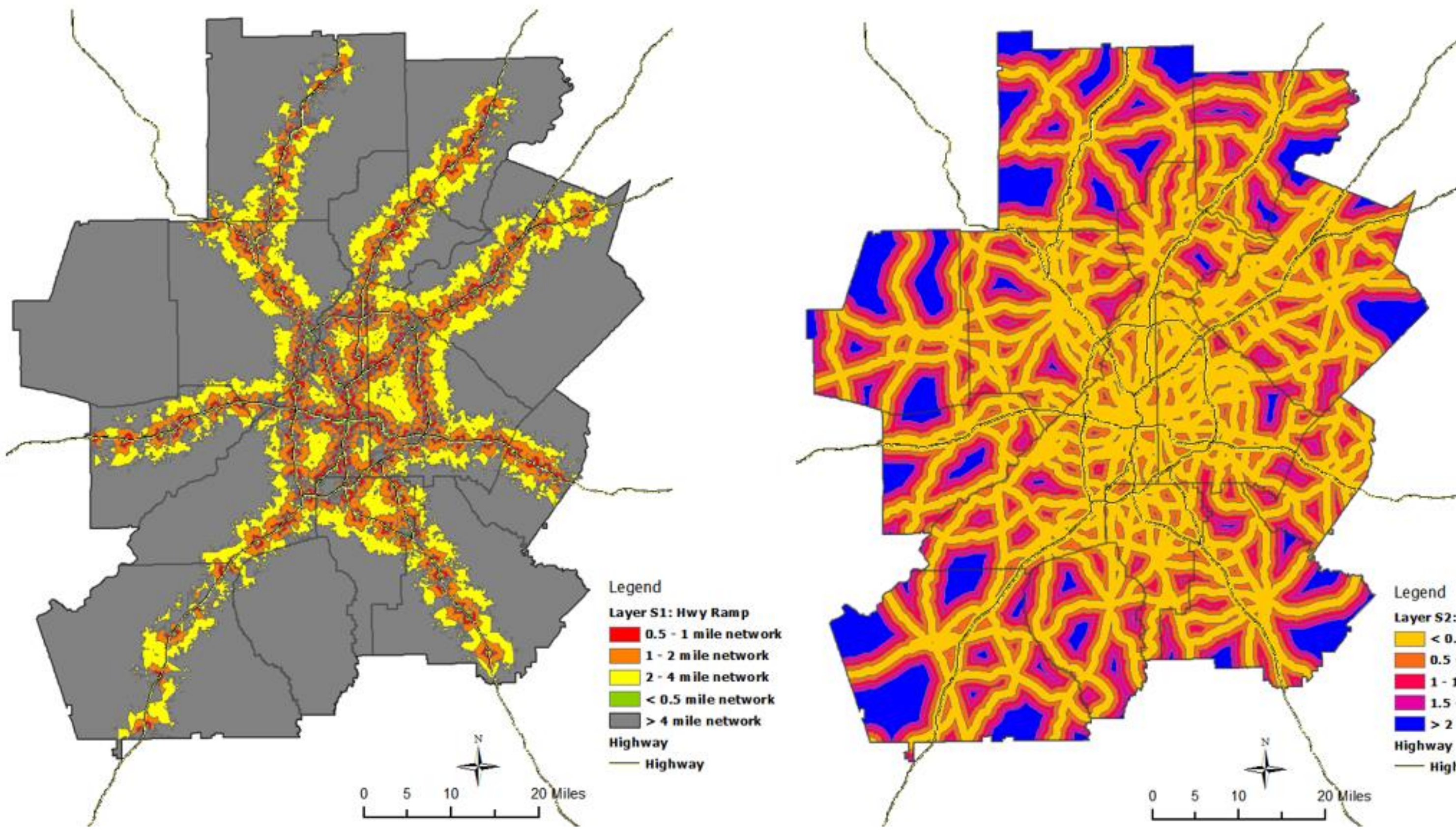


Figure 47. Suitability layer S1 (Highway Ramp) and S2 (Major Roads)

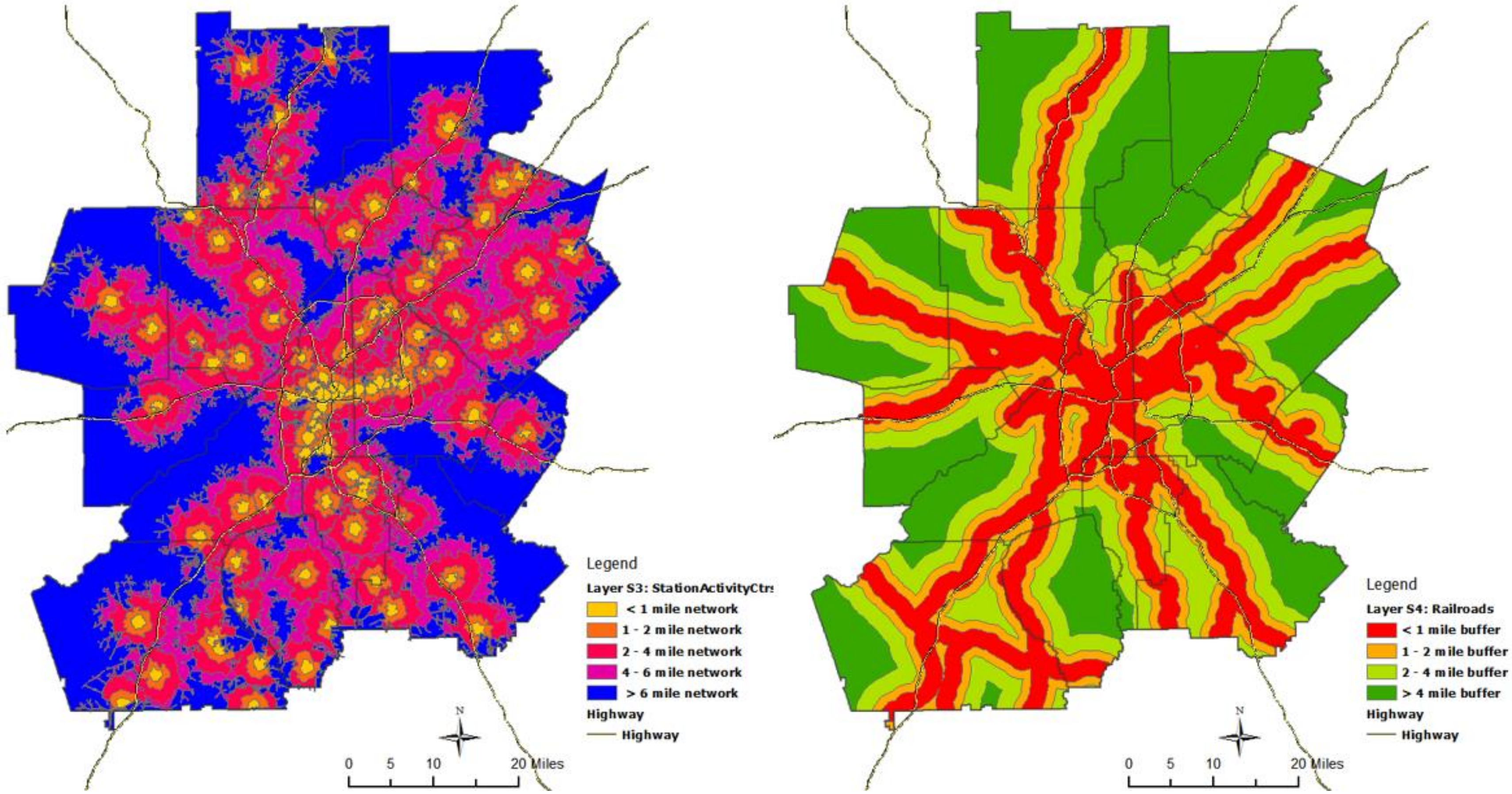


Figure 48. Suitability layer S3 (Station-activity center) and S4 (Railroads)

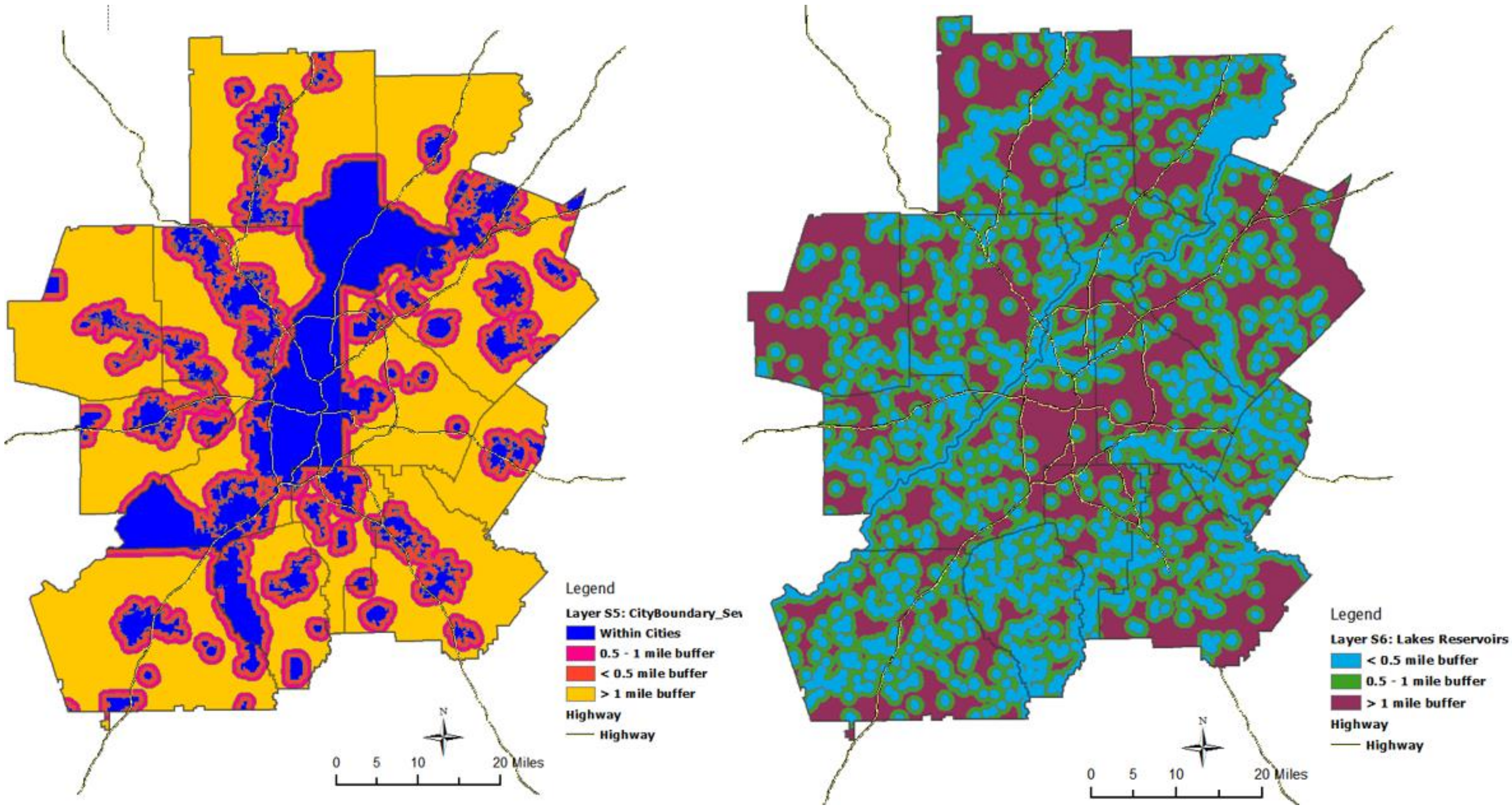


Figure 49. Suitability layer S5 (City Boundary-Sewer) and S6 (Lakes Reservoirs)

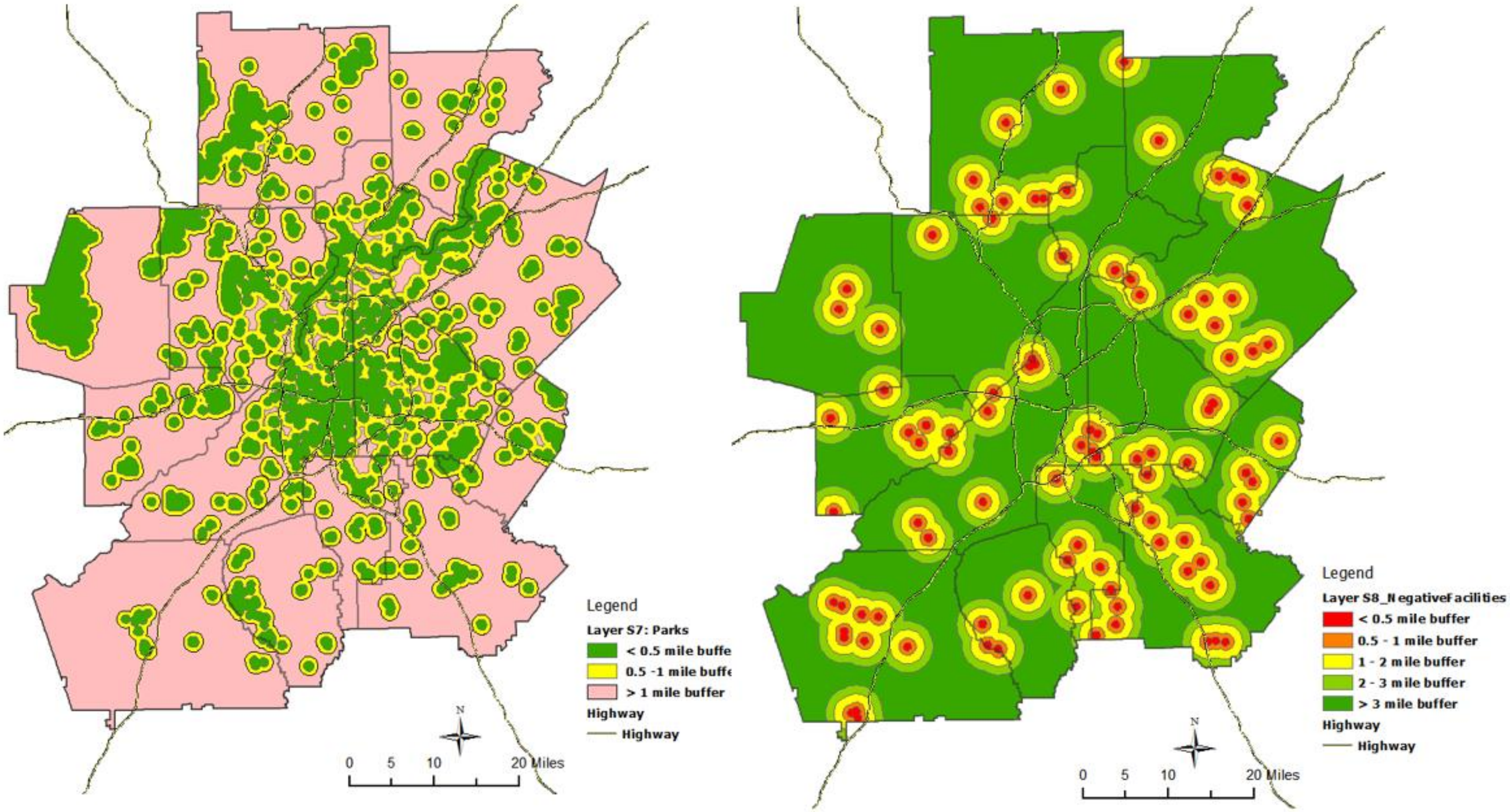


Figure 50. Suitability layer S7 (Parks) and S8 (Negative Facilities)

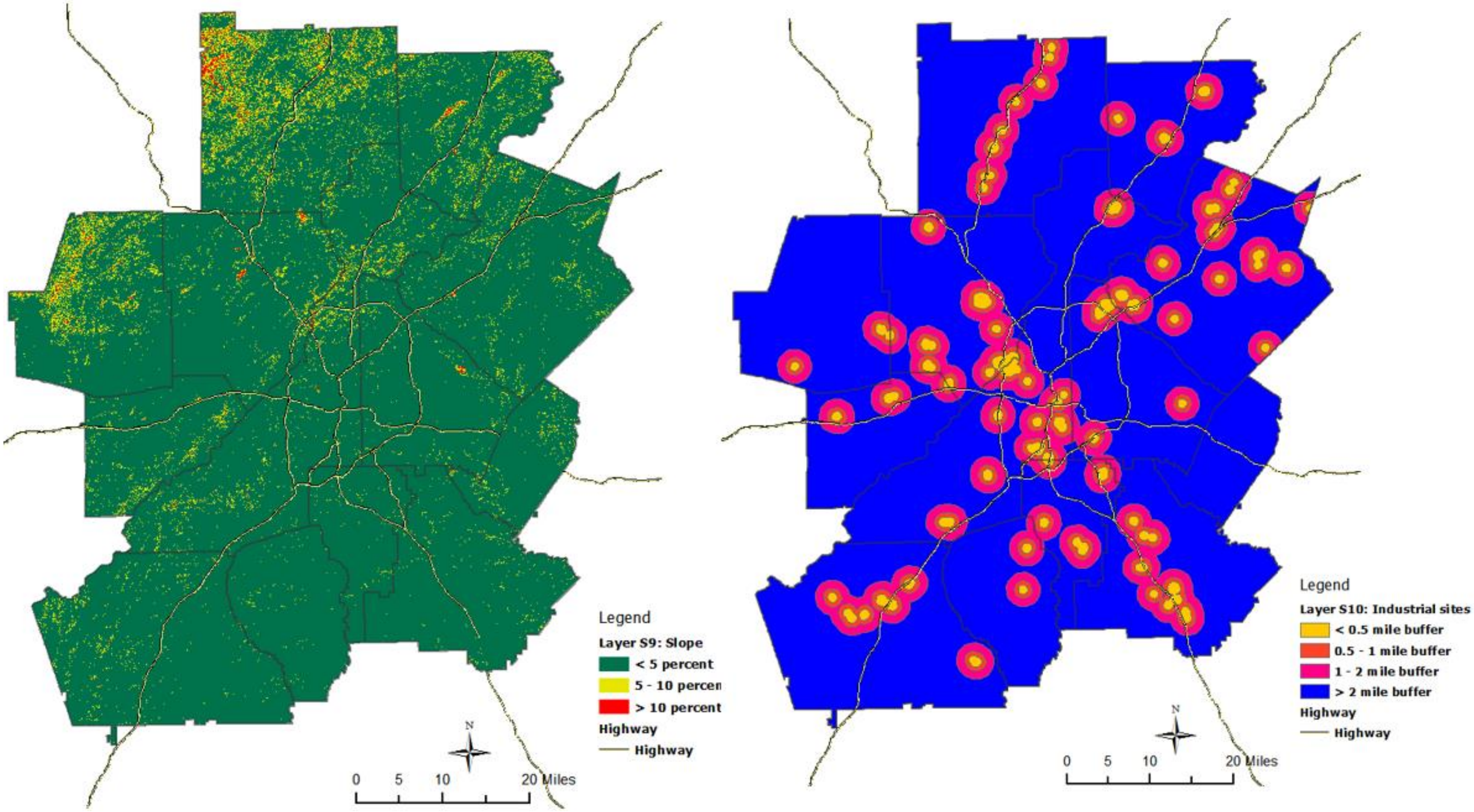
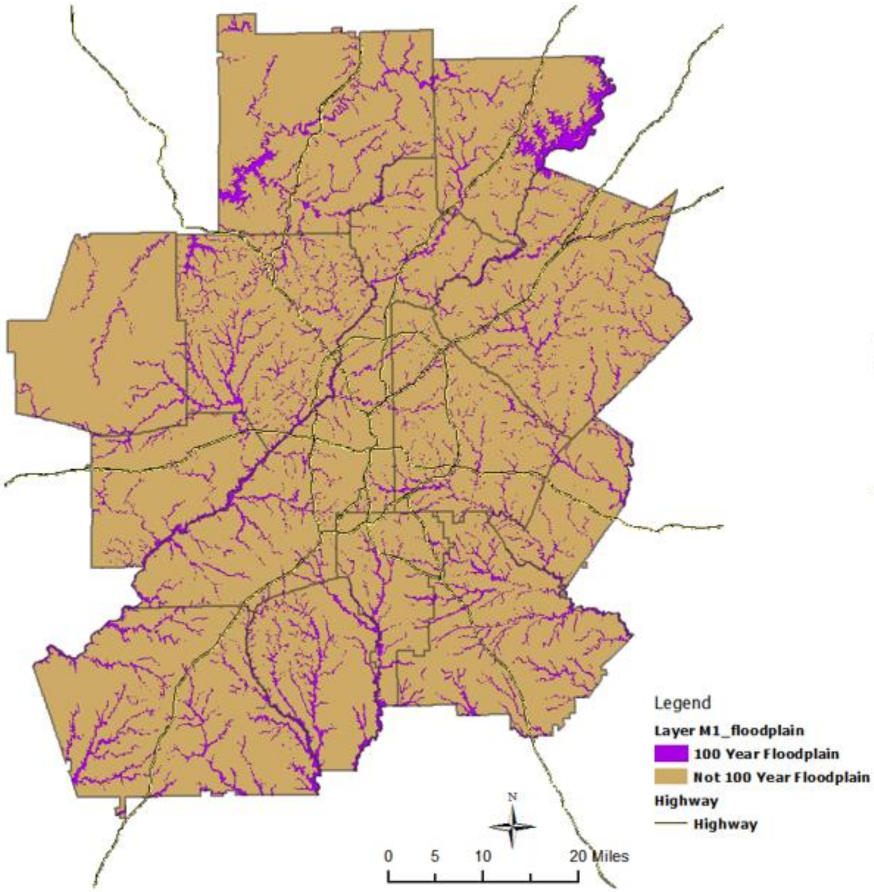


Figure 51. Suitability layer S9 (Slope) and S10 (Industrial sites)



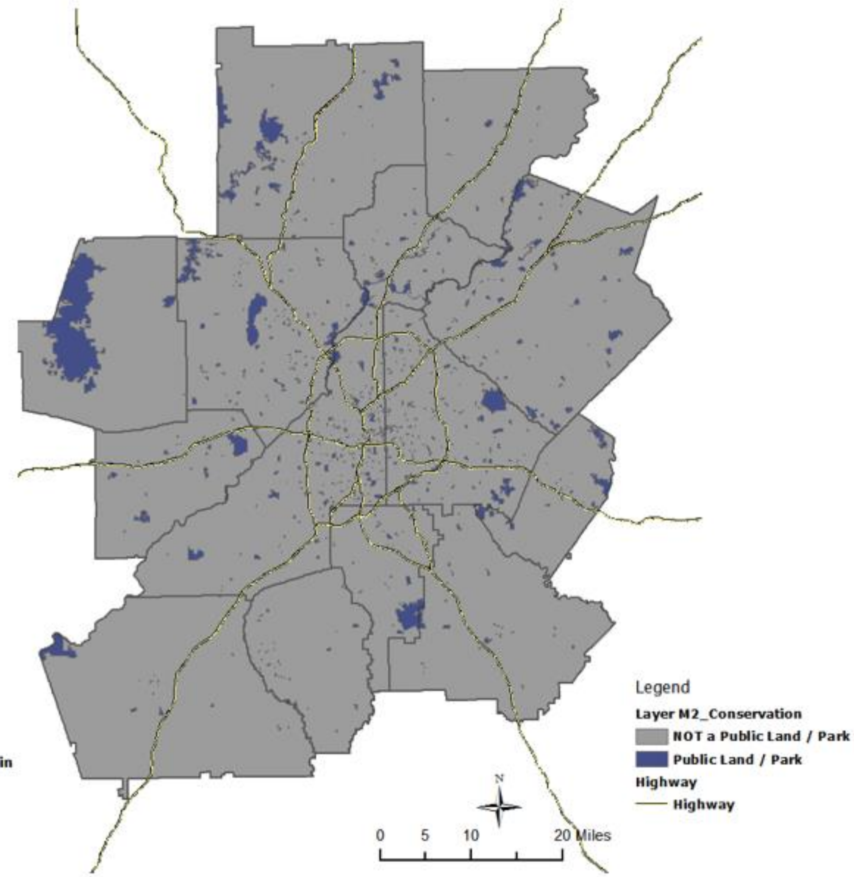


Figure 52. Suitability layer M1 (Floodplain) and M2 (Conservation)

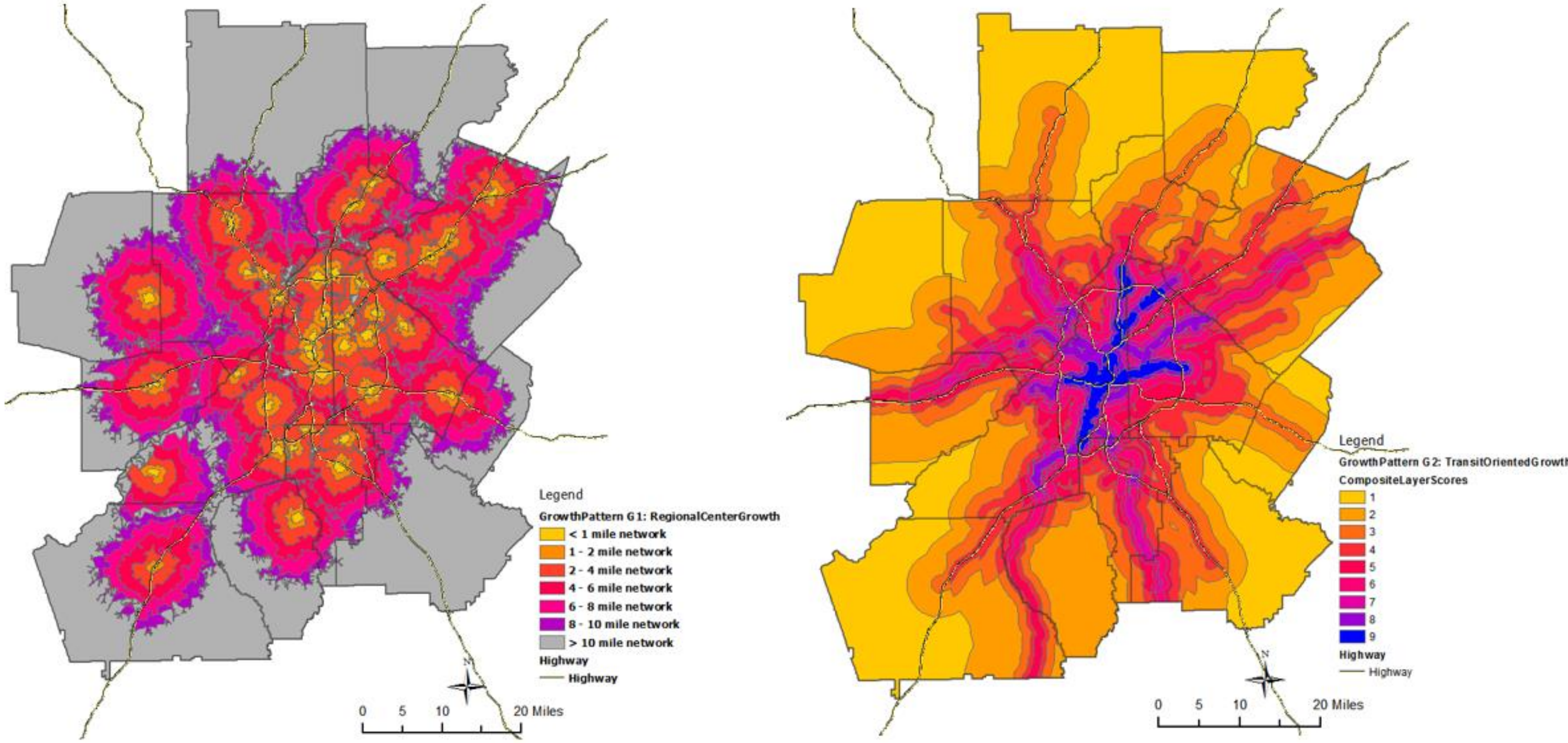


Figure 53. Suitability layer G1 (Regional Center-Oriented Growth) and G2 (Transit-oriented Growth)

Table 47. Suitability AHP matrix for single family residential land use

Factor	G1_growth_pattern_layer	S1_interstate highway ramps	S2_major_roads	S3_stations_activity centers	S4_railroads	S5_city boundaries_sewered	S6_lakes_reservoirs	S7_parks	S8_negative_facilities	S9_slope	S10_existing_industrial	AHP (Coefficient)	Consistency Measure
G1_growth_pattern_layer	1	2	1	3	4	2	3	3	4	5	4	**0.193**	11.205
S1_interstate hwy ramps	1/2	1	1/2	2	3	1	2	2	3	4	3	**0.121**	11.188
S2_major_roads	1	2	1	3	4	2	3	3	4	5	4	**0.193**	11.205
S3_stations_activity centers	1/3	1/2	1/3	1	2	1/2	1	1	2	3	2	**0.072**	11.100
S4_railroads	1/4	1/3	1/4	1/2	1	1/3	1/2	1/2	1	2	1	**0.042**	11.052
S5_city boundaries_sewered	1/2	1	1/2	2	3	1	2	2	3	4	3	**0.121**	11.188
S6_lakes_reservoirs	1/3	1/2	1/3	1	2	1/2	1	1	2	3	2	**0.072**	11.100
S7_parks	1/3	1/2	1/3	1	2	1/2	1	1	2	3	2	**0.072**	11.100
S8_negative_facilities	1/4	1/3	1/4	1/2	1	1/3	1/2	1/2	1	2	1	**0.042**	11.052
S9_slope	1/5	1/4	1/5	1/3	1/2	1/4	1/3	1/3	1/2	1	1/2	**0.027**	11.080
S10_existing_industrial	1/4	1/3	1/4	1/2	1	1/3	1/2	1/2	1	2	1	**0.042**	11.052

Lambda 11.12 CI = 0.01 RI = 1.52 CI/RI = 0.008

Table 48. Suitability AHP matrix for multi-family residential land use

Factor	G1_growth_pattern layer	S1_interstate hwy ramps	S2_major_roads	S3_stations_activity centers	S4_railroads	S5_city boundaries sewered	S6_lakes_reservoirs	S7_parks	S8_negative_facilities	S9_slope	S10_existing_industrial	AHP (Coefficient)	Consistency Measure
G1_growth_pattern_layer	1	2	2	1	3	3	5	4	3	5	4	**0.194**	11.2721
S1_interstate hwy ramps	1/2	1	1	1/2	2	2	4	3	2	4	3	**0.122**	11.2685
S2_major_roads	1/2	1	1	1/2	2	2	4	3	2	4	3	**0.122**	11.2685
S3_stations_activity centers	1	2	2	1	3	3	5	4	3	5	4	**0.194**	11.2721
S4_railroads	1/3	1/2	1/2	1/3	1	1	3	2	1	3	2	**0.074**	11.1750
S5_city boundaries_sewered	1/3	1/2	1/2	1/3	1	1	3	2	1	3	2	**0.074**	11.1750
S6_lakes_reservoirs	1/5	1/4	1/4	1/5	1/3	1/3	1	1/2	1/3	1	1/2	**0.028**	11.1030
S7_parks	1/4	1/3	1/3	1/4	1/2	1/2	2	1	1/2	3	1	**0.047**	11.0449
S8_negative_facilities	1/3	1/2	1/2	1/3	1	1	3	2	1	3	2	**0.074**	11.1750
S9_slope	1/5	1/4	1/4	1/5	1/3	1/3	1	1/3	1/3	1	1/2	**0.028**	11.0859
S10_existing_industrial	1/4	1/3	1/3	1/4	1/2	1/2	2	1	1/2	2	1	**0.044**	11.0886
				Lambda =	11.18		CI =	0.02	RI =	1.52		CI/RI =	0.0115

Table 49. Suitability AHP matrix for Construction, manufacturing, and wholesales land use

Factor	G1_growth_pattern layer	S1_interstate hwy ramps	S2_major_roads	S3_stations_activity centers	S4_railroads	S5_city boundaries_sewered	S6_lakes_reservoirs	S7_parks	S8_negative_facilities	S9_slope	S10_existing_industrial	AHP (Coefficient)	Consistency Measure
G1_growth_pattern_layer	1	1/2	1/2	2	1/3	1/2	1/4	1	1/3	2	1/4	**0.044**	11.0502
S1_interstate hwy ramps	2	1	1	3	1/2	1	1/3	2	1/2	3	1/3	**0.074**	11.1275
S2_major_roads	2	1	1	3	1/2	1	1/3	2	1/2	3	1/3	**0.074**	11.1275
S3_stations_activity centers	1/2	1/3	1/3	1	1/4	1/3	1/5	1/2	1/4	1	1/5	**0.028**	11.0773
S4_railroads	3	2	2	4	1	2	1/2	3	1	4	1/2	**0.122**	11.2290
S5_city boundaries_sewered	2	1	1	3	1/2	1	1/3	2	1/2	3	1/3	**0.074**	11.1275
S6_lakes_reservoirs	4	3	3	5	2	3	1	4	2	5	1	**0.194**	11.2426
S7_parks	1	1/2	1/2	2	1/3	1/2	1/4	1	1/3	2	1/4	**0.044**	11.0502
S8_negative_facilities	3	2	2	4	1	2	1/2	3	1	4	1/2	**0.122**	11.2290
S9_slope	1/2	1/3	1/3	1	1/4	1/3	1/5	1/2	1/4	1	1/5	**0.028**	11.0773
S10_existing_industrial	4	3	3	5	2	3	1	4	2	5	1	**0.194**	11.2426
				Lambda =	11.14		CI =	0.01	RI =	1.52		CI/RI =	0.0095

Table 50. TCU, Retail, FIRE (finance-real estate), and Government/Public Land use Suitability AHP matrix

Factor	G1_growth_pattern layer	S1_interstate hwy ramps	S2_major_roads	S3_stations_activity centers	S4_railroads	S5_city boundaries_sewered	S6_lakes_reservoirs	S7_parks	S8_negative_facilities	S9_slope	S10_existing_industrial	AHP (Coefficient)	Consistency Measure
G1_growth_pattern_layer	1	2	3	1	3	2	4	4	3	5	5	**0.193**	11.3014
S1_interstate hwy ramps	1/2	1	2	1/2	2	1	3	3	2	4	4	**0.122**	11.3078
S2_major_roads	1/3	1/2	1	1/3	1	1/2	2	2	1	3	3	**0.073**	11.2224
S3_stations_activity centers	1	2	3	1	3	2	4	4	3	5	5	**0.193**	11.3014
S4_railroads	1/3	1/2	1	1/3	1	1/2	2	2	1	3	3	**0.073**	11.2224
S5_city boundaries/sewered	1/2	1	2	1/2	2	1	3	3	2	4	4	**0.122**	11.3078
S6_lakes_reservoirs	1/4	1/3	1/2	1/4	1/2	1/3	1	1	1/2	2	2	**0.044**	11.1268
S7_parks	1/4	1/3	1/2	1/4	1/2	1/3	1	1	1/2	3	3	**0.050**	11.0370
S8_negative_facilities	1/3	1/2	1	1/3	1	1/2	2	2	1	3	3	**0.073**	11.2224
S9_slope	1/5	1/4	1/3	1/5	1/3	1/4	1/2	1/3	1/3	1	1	**0.028**	11.0985
S10_existing_industrial	1/5	1/4	1/3	1/5	1/3	1/4	1/2	1/3	1/3	1	1	**0.028**	11.0985
				Labmda	11.20		CI =	0.02	RI =	1.52		CI/RI =	0.0134

Table 51. Suitability Factor Weights and Ratings: Residential uses

	Factor Layer		Single Family Residential			Multi-Family Residential		
		Proximity	AHP Factor Weight	Classification	Rating	AHP Weight	Classification	Rating
M1	Floodplain, Public Lan	Dichotomy (Boolean)		True/False			True/False	
G1 G2	Growth pattern layer (Reg. centers or Transit-Oriented)	Network Distance	**0.193**	1-mile interval	10 (least preferred) ~ 90 (most	**0.194**	1-mile interval	10 (least preferred) ~ 90 (most
S1	Interstate Hwy Exit Ramps	Network Distance	**0.121**	< 0.5 mile Network	60	**0.122**	< 0.5 mile Network	70
				1 mile Network	70		1 mile Network	80
				2 mile Network	80		2 mile Network	90
				4 mile Network	90		4 mile Network	80
				> 4 mile Network	80		> 4 mile Network	60
S2	Major Roads	Buffer Distance	**0.193**	< 0.5 mile Buffer	70	**0.122**	< 0.5 mile Buffer	70
				1 mile Buffer	90		1 mile Buffer	90
				1.5 mile Buffer	90		1.5 mile Buffer	90
				2 mile Buffer	80		2 mile Buffer	80
				>2 mile Buffer	70		>2 mile Buffer	70
S3	Station/Town/Activit y Centers	Network Distance	**0.072**	1 mile Network	60	**0.194**	1 mile Network	80
				2 mile Network	70		2 mile Network	80
				4 mile Network	90		4 mile Network	70
				6 mile Network	90		6 mile Network	70
				> 6 mile Network	60		> 6 mile Network	50
S4	Railroads	Buffer Distance	**0.042**	1 mile Buffer	30	**0.074**	1 mile Buffer	30
				2 mile Buffer	70		2 mile Buffer	70
				4 mile Buffer	90		4 mile Buffer	90
				>4 mile Buffer	90		>4 mile Buffer	90
S5	City boundaries-Sewered Areas	Buffer Distance	**0.121**	Sewered Areas	80	**0.074**	Sewered Areas	80
				0.5 mile Buffer	70		0.5 mile Buffer	70
				1 mile Buffer	70		1 mile Buffer	70
				>1 mile Buffer	30		>1 mile Buffer	30
S6	Lakes/Ponds/Reservoirs	Buffer Distance	**0.072**	< 0.5 mile buffer	90	**0.028**	0.5 mile buffer	90
				1 mile buffer	70		1 mile buffer	70
				> 1 mile buffer	10		> 1 mile buffer	10
S7	Parks	Buffer Distance	**0.072**	< 0.5 mile Buffer	90	**0.047**	0.5 mile Buffer	90
				1 mile buffer	70		1 mile buffer	70
				> 1 mile buffer	30		> 1 mile buffer	30
S8	Negative Facilities (Landfill/ Wastewater Treat Plant)	Buffer Distance	**0.042**	0.5 mile Buffer	10	**0.074**	0.5 mile Buffer	10
				1 mile Buffer	30		1 mile Buffer	30
				2mile Buffer	70		2mile Buffer	70
				3 mile Buffer	90		3 mile Buffer	90
				>3 mile Buffer	90		>3 mile Buffer	90
S9	Slope	100-foot resolutior	**0.027**	< 5 % slope	90	**0.028**	< 5 % slope	90
				5 -10 % slope	70		5 -10 % slope	70
				> 10 % slope	30		> 10 % slope	30
S10	Proximity to Existing Industrial Use	Buffer Distance	**0.042**	< 0.5 mile Buffer	10	**0.044**	< 0.5 mile Buffer	10
				0.5 - 1 mile buffer	30		0.5 - 1 mile buffer	30
				1- 2 mile buffer	60		1- 2 mile buffer	60
				> 2 mile buffer	90		> 2 mile buffer	90

Table 52. Suitability Factor Weights and Ratings: Non-Residential uses

			Retail, ,FIRE, Services,TCU and Gov. Public			Construction, Manufactoring, and Wholesales		
	Factor Layer	Proximity Measure	AHP Factor Weight	Classification	Rating	AHP Factor Weight	Classification	Rating
M1	Floodplain, Public La	Dichotomy (Boolean)		True/False			True/False	
G1 G2	Growth pattern (Reg.centers or Transit-Oriented)	Network Distance	0.193	1-mile interval	10 (least preferred) ~ 90 (most preferred)	0.044	1-mile interval	10 (least preferred) ~ 90 (most preferred)
S1	Interstate Hwy Exit Ramps	Network Distance	0.122	< 0.5 mile Network	90	0.074	< 0.5 mile Network	50
				1 mile Network	80		1 mile Network	60
				2 mile Network	50		2 mile Network	70
				4 mile Network	50		4 mile Network	80
				> 4 mile Network	30		> 4 mile Network	90
S2	Major Roads	Buffer Distance	0.073	< 0.5 mile Buffer	90	0.074	< 0.5 mile Buffer	90
				1 mile Buffer	90		1 mile Buffer	90
				1.5 mile Buffer	70		1.5 mile Buffer	70
				2 mile Buffer	50		2 mile Buffer	50
				>2 mile Buffer	30		>2 mile Buffer	50
S3	Station/Town/Activity Centers	Network Distance	0.193	1 mile Network	90	0.028	1 mile Network	20
				2 mile Network	90		2 mile Network	50
				4 mile Network	70		4 mile Network	70
				6 mile Network	50		6 mile Network	70
				> 6 mile Network	30		> 6 mile Network	90
S4	Railroads	Buffer Distance	0.073	1 mile Buffer	70	0.122	1 mile Buffer	90
				2 mile Buffer	90		2 mile Buffer	80
				4 mile Buffer	90		4 mile Buffer	70
				>4 mile Buffer	70		>4 mile Buffer	30
S5	City boundaries-Sewered Areas	Buffer Distance	0.122	Sewered Areas	90	0.074	Sewered Areas	80
				0.5 mile Buffer	80		0.5 mile Buffer	70
				1 mile Buffer	60		1 mile Buffer	60
				>1 mile Buffer	30		>1 mile Buffer	50
S6	.akes/Ponds/Reservoir	Buffer Distance	0.044	< 0.5 mile buffer	10	0.194	0.5 mile buffer	90
				1 mile buffer	70		1 mile buffer	70
				> 1 mile buffer	90		> 1 mile buffer	10
S7	Parks	Buffer Distance	0.050	< 0.5 mile Buffer	10	0.044	0.5 mile Buffer	10
				1 mile buffer	70		1 mile buffer	70
				> 1 mile buffer	90		> 1 mile buffer	90
S8	Negative Facilities (Landfill/ Wastewater Treat Plant)	Buffer Distance	0.073	0.5 mile Buffer	10	0.122	0.5 mile Buffer	90
				1 mile Buffer	50		1 mile Buffer	80
				2mile Buffer	70		2mile Buffer	70
				3 mile Buffer	80		3 mile Buffer	50
				>3 mile Buffer	90		>3 mile Buffer	30
S9	Slope	100-foot resolution	0.028	< 5 % slope	90	0.028	< 5 % slope	90
				5 -10 % slope	70		5 -10 % slope	70
				> 10 % slope	30		> 10 % slope	30
S10	Proximity to Existing Industrial Use	Buffer Distance	0.028	< 0.5 mile Buffer	10	0.194	< 0.5 mile Buffer	90
				0.5 - 1 mile buffer	30		0.5 - 1 mile buffer	80
				1- 2 mile buffer	60		1- 2 mile buffer	70
				> 2 mile buffer	90		> 2 mile buffer	60

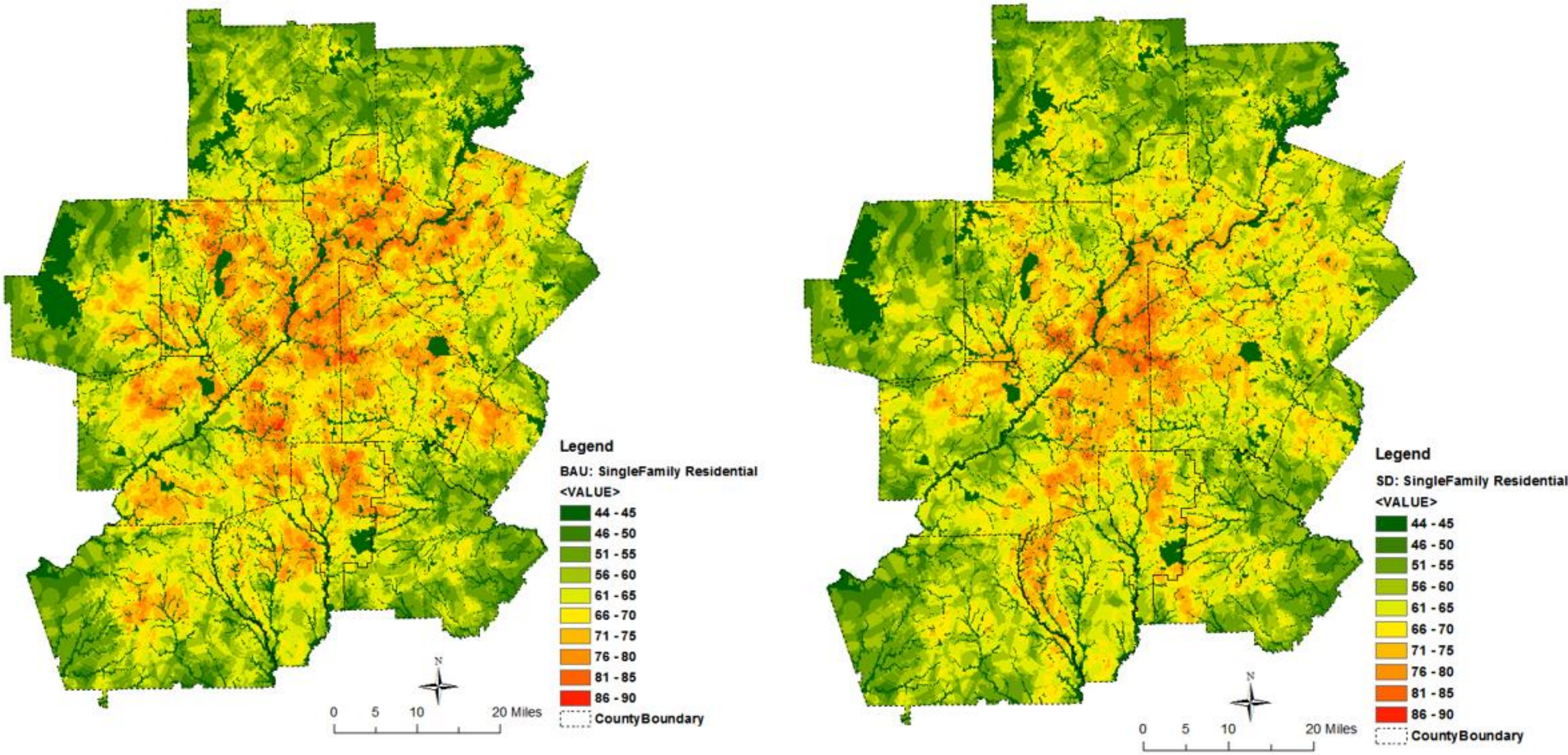


Figure 54. Final Suitability Score layers for single family use (BAU and SD scenario)

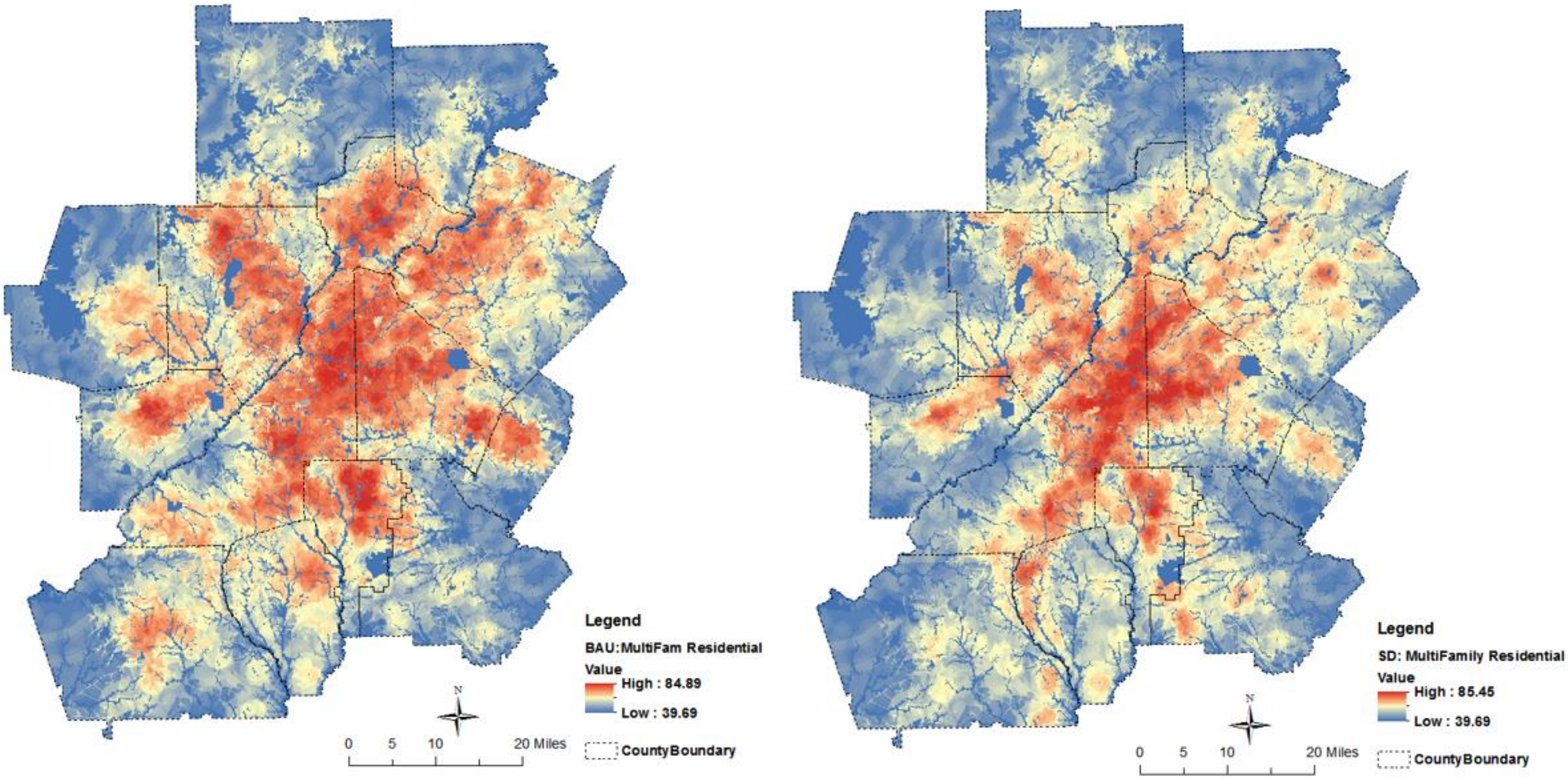


Figure 55. Final Suitability Score layers for multi-family use (BAU and SD scenario)

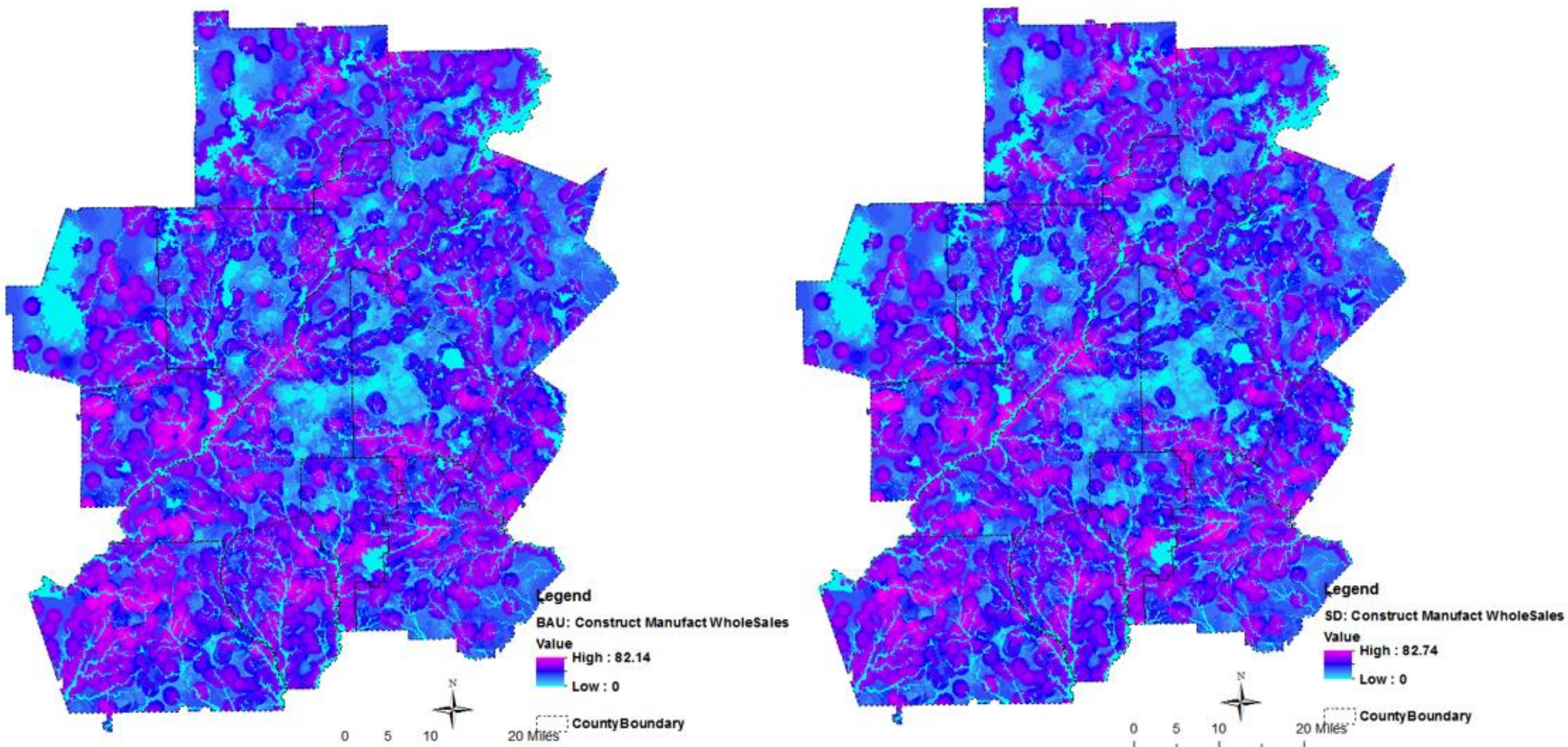


Figure 56. Final Suitability Score layers for construction, manufacturing, and wholesales use (BAU and SD scenario)

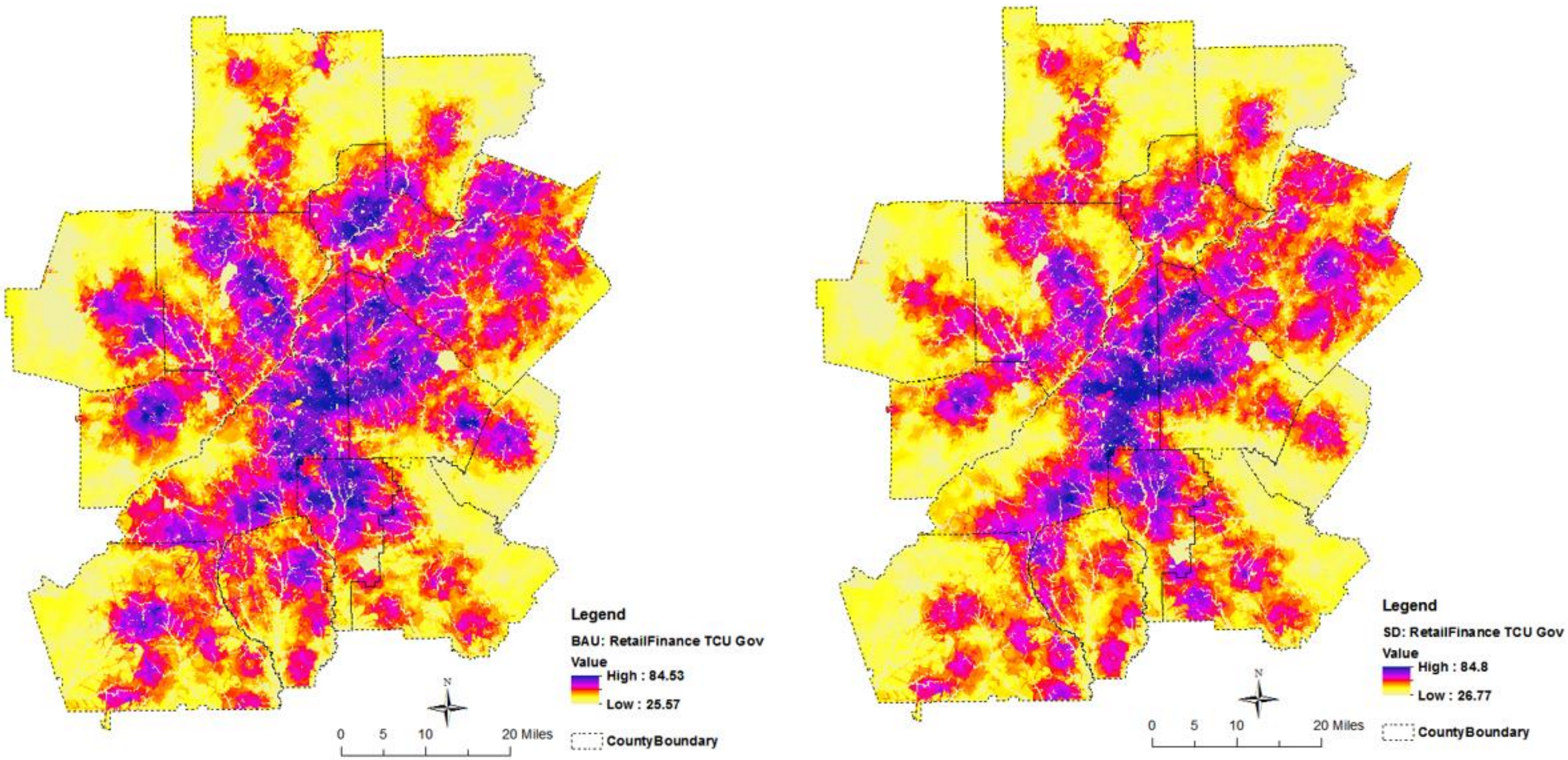


Figure 57. Final Suitability Score layers for Retail, FIRE, Services, TCU, and Government (BAU and SD scenario)

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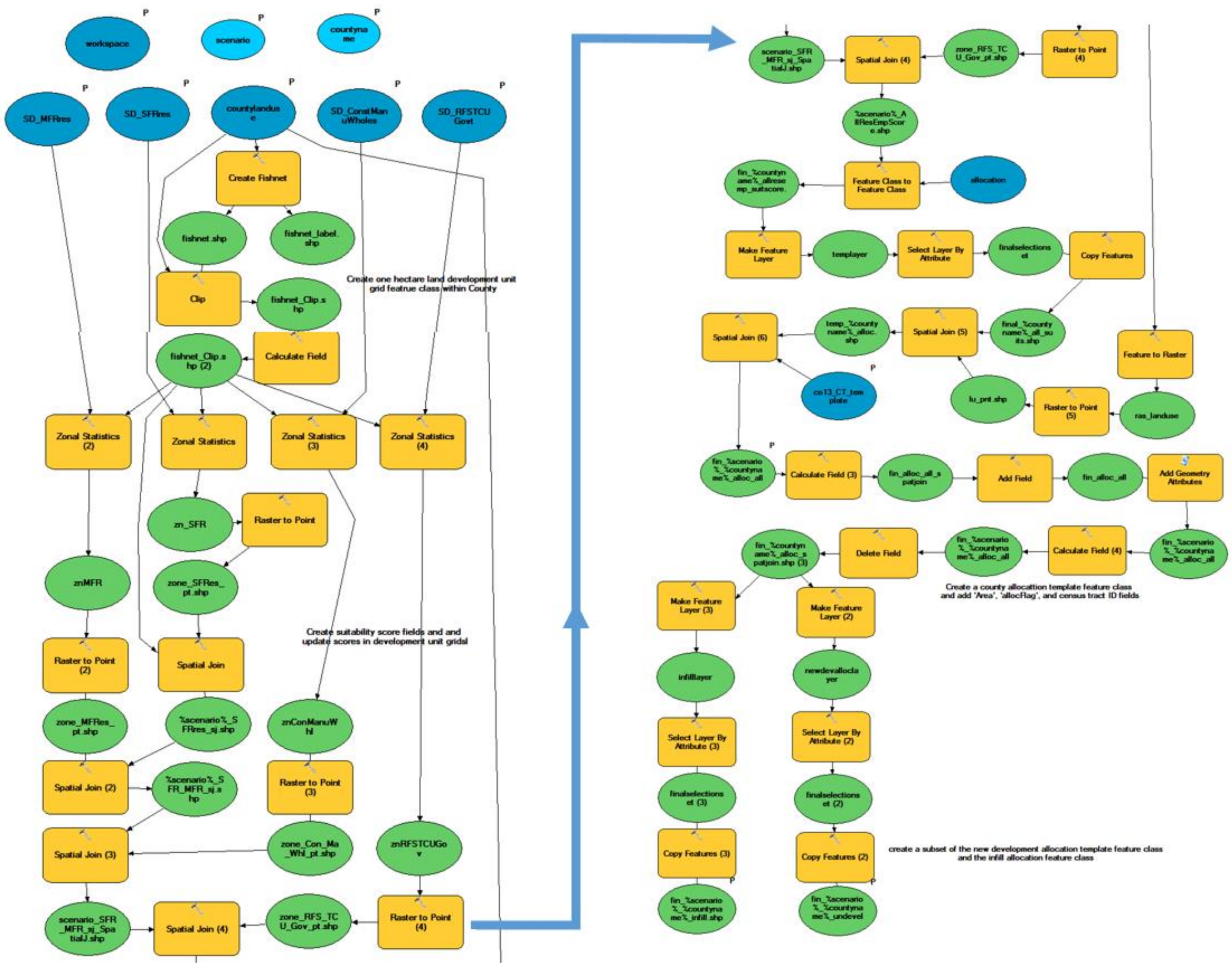

Figure 58. Example of Model Builder model in suitability module: Suitability Summary Statistics Score Layer Generation

APPENDIX B

BAU														
Year\ County	**Cherokee**	**Clayton**	**Cobb**	**Coweta**	**DeKalb**	**Douglas**	**Fayette**	**Forsyth**	**Fulton**	**Gwinnett**	**Henry**	**Paulding**	**Rockdale**	**Year Total**
Year 2010	20,602,546	32,613,979	84,403,501	12,931,777	88,773,865	13,548,415	12,729,379	22,680,531	161,459,951	94,225,520	19,704,048	12,305,565	9,846,176	585,825,255
Year 2015	25,748,997	35,593,433	96,439,306	15,200,838	101,251,947	16,068,841	14,228,266	27,954,563	190,323,640	113,557,109	23,955,209	14,646,135	11,066,768	686,035,052
Year 2020	29,327,833	37,506,360	102,886,515	17,357,904	107,027,590	17,634,951	15,519,263	33,851,041	201,297,457	123,382,096	27,638,282	16,653,583	12,029,688	742,112,561
Year 2025	33,417,189	39,463,991	109,115,320	20,037,761	110,981,748	19,670,940	17,043,213	41,470,827	209,861,419	133,091,065	32,662,580	19,296,724	13,308,563	799,421,341
Year 2030	37,472,962	41,314,823	116,098,827	22,553,700	115,355,171	21,838,259	18,794,102	48,654,432	221,428,652	143,808,221	37,584,636	21,723,783	14,618,122	861,245,691
Year 2035	41,955,696	42,492,275	121,824,120	25,068,611	121,278,809	23,722,621	19,999,269	54,836,297	239,334,735	156,930,377	41,388,562	24,211,912	15,700,012	928,743,296
Year 2040	46,407,888	44,427,060	128,628,551	27,667,781	128,322,920	25,315,373	21,334,588	59,200,641	256,625,995	170,583,511	45,538,722	26,769,658	16,736,398	997,559,087
County Total	234,933,111	273,411,922	759,396,140	140,818,373	772,992,049	137,799,400	119,648,080	288,648,333	1,480,331,848	935,577,900	228,472,040	135,607,360	93,305,727	5,600,942,283

Table 53. Water demand projection in gallon per day in 13 counties: BAU Scenario

Table 54. Water demand projection in gallon per day in 13 counties: SD Scenario

SD Scenario														
Year\ County	**Cherokee**	**Clayton**	**Cobb**	**Coweta**	**DeKalb**	**Douglas**	**Fayette**	**Forsyth**	**Fulton**	**Gwinnett**	**Henry**	**Paulding**	**Rockdale**	**Year Total**
Year 2010	20,602,546	32,613,979	84,403,501	12,931,777	88,773,865	13,548,415	12,729,379	22,680,531	161,459,951	94,225,520	19,704,048	12,305,565	9,846,176	585,825,255
Year 2015	22,577,917	31,761,789	85,616,670	13,471,198	89,837,490	14,191,429	12,677,346	24,553,014	167,609,052	100,032,458	21,085,619	12,938,881	9,850,316	606,203,178
Year 2020	25,435,576	33,264,173	90,727,114	15,117,582	94,369,035	15,424,200	13,695,642	29,049,723	175,944,824	107,715,744	24,017,771	14,564,795	10,635,496	649,961,677
Year 2025	28,655,676	34,831,271	95,609,033	17,134,109	97,489,731	16,981,474	14,892,171	34,792,289	182,477,043	115,215,475	27,966,206	16,649,156	11,652,697	694,346,333
Year 2030	31,858,132	36,302,405	101,051,264	19,016,629	100,929,815	18,688,010	16,237,108	40,234,039	191,091,056	123,515,766	31,823,332	18,516,929	12,684,898	741,949,383
Year 2035	35,386,661	37,253,342	105,560,015	20,921,918	105,558,277	18,688,010	17,204,727	44,971,862	204,021,384	133,635,479	34,837,953	20,430,299	13,528,696	791,998,624
Year 2040	38,909,820	38,822,951	110,919,498	22,870,545	111,060,426	18,688,010	18,272,867	48,306,474	216,514,517	144,136,925	38,106,093	22,410,346	14,334,863	843,353,337
County Total	203,426,329	244,849,911	673,887,097	121,463,758	688,018,640	116,209,547	105,709,241	244,587,932	1,299,117,827	818,477,368	197,541,024	117,815,970	82,533,143	4,913,637,786

Table 55. Water demand projection in gallon per day in 13 counties: SD + RWH Scenario

SD with RWH														
Year \ County	Cherokee	Clayton	Cobb	Coweta	DeKalb	Douglas	Fayette	Forsyth	Fulton	Gwinnett	Henry	Paulding	Rockdale	Year Total
Year 2010	18,374,397	30,425,772	78,900,314	11,121,499	83,602,720	12,011,068	11,281,203	19,516,487	153,213,441	87,354,439	17,239,656	10,322,010	8,846,975	542,209,982
Year 2015	19,966,019	29,472,709	79,614,181	11,815,877	84,300,985	12,504,455	11,158,695	22,838,247	158,474,368	92,419,573	18,802,790	11,098,804	8,814,356	561,281,056
Year 2020	22,545,602	30,886,938	84,406,360	13,390,286	88,678,888	13,649,470	12,137,860	26,963,615	166,523,975	99,422,247	21,672,372	12,570,016	9,560,645	602,408,275
Year 2025	25,434,099	32,390,187	88,957,090	15,238,045	91,689,759	15,068,776	13,269,677	31,838,313	172,841,897	105,896,951	25,425,383	14,178,599	10,528,478	642,757,254
Year 2030	28,198,192	33,768,977	94,030,010	16,981,690	94,999,378	16,620,549	14,522,863	36,152,195	181,141,743	112,931,587	28,955,955	15,621,676	11,508,935	685,433,747
Year 2035	31,291,057	34,673,402	98,216,641	18,708,149	99,401,933	16,620,549	15,439,111	39,781,509	193,302,049	120,623,635	31,736,290	16,712,543	12,310,436	728,817,303
Year 2040	34,161,717	36,160,630	103,206,187	20,454,921	104,590,295	16,620,549	16,447,241	42,113,492	204,944,412	127,731,643	34,566,592	17,334,503	13,070,568	771,402,749
County Total	179,971,083	227,778,614	627,330,784	107,710,467	647,263,957	103,095,415	94,256,649	219,203,858	1,230,441,884	746,380,075	178,399,038	97,838,151	74,640,392	4,534,310,366

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